ESSAYS ON THE COSTS AND BENEFITS OF CLEANER ENERGY

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Abstract

Undertaking a major clean energy transition in both developing countries and developed countries is challenging. Well-designed policies weigh the cost and benefit of every alternative. My dissertation considers different aspects of such transitions in two very different contexts: a nationwide transition from kerosene to cleaner burning propane in Indonesia, and a transition from a fossil fuel to 100 percent renewable electric system in Hawaii. As for the benefits of cleaner energy, it helps us to understand to what extent a cleaner fuel transition could improve people's health and their well-being, and sheds light on some possible channels through which better health arises. As for the cost of cleaner energy, it also demonstrates how efficient variable pricing can lower the cost of clean renewable energy. To assess how efficient pricing affects the cost of renewable power, I introduce a new computational modeling tool that can simultaneously consider key features of a real-time power system and a realistic characterization of demand with potentially flexible end uses. The model is generalizable and can be easily adapted to other settings.

Chapter 2 studies the impact of a household fuel conversion program on infant mortality by examining a kerosene to liquid petroleum gas (LPG) conversion program in Indonesia, one of the largest household energy transition projects ever attempted in the developing world. Chapter 3 examines the extent to which variable pricing can make renewable energy more cost effective in the state of Hawaii. It uses a novel model of power supply and demand that simultaneously optimizes investment in generation capacity, storage capacity, and real-time

operation of the system, a demand system that accounts for interhour elasticity and overall demand elasticity. Lastly, chapter 4 investigates on the extent to which the switching improves households well-being. Using a nationwide transition from kerosene to cleaner burning propane in Indonesia, the same program as in chapter 2, I investigate households consumption response to fuel switching.

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Chapter 1

Introduction

> *"Energy is crucial for achieving almost all of the Sustainable Development Goals, from its role in the eradication of poverty through advancements in health, education, water supply and industrialization, to combating climate change."*(Economic and Council, 2016)

The seventh United Nation Sustainable Development Goals is to ensure access to affordable, reliable, sustainable and modern energy for all by 2030. Although the importance of the modern energy is emphasized as in above quote, the proportion of the worlds population with access to clean fuels and technologies for cooking has only increased from 51 per cent in 2000 to 58 per cent in 2014. Similarly, the share of renewable energy such as biofuels, wind, solar PV, hydropower has also increased slowly, from 17.4 per cent in 2000 to 18.1 per cent in 2012 (Economic and Council, 2016). Although we are progressing, we are still far away from achieving the goal. One reason beneath the slow progress is that there is not enough rigorous analysis on the cost and benefit of having cleaner energy. This creates uncertainty to the policy makers on what kind of intervention that are cost-effective. Growing concern about all forms of air pollution, as different forms of it are increasingly linked to poor health outcomes and lower productivity, as well as other ecological and environmental impacts. When we dicuss about the economic cost of air pollution, the impact on mortality as reflected by the Value of Statistical Live (VSL) is predominant. Up until now, we have not been able to know precisely by how much. The most recent estimation by the World Bank and team, air pollution costs more than USD 5 trillion in welfare losses (Bank and IHME, 2016). That is about the size of the gross domestic product of India, Canada, and Mexico. Good news that the cost of renewable energy technology like wind, solar PV, and batteries are falling, the cost of clean air is likely not as high as it is used to be.

My dissertation considers different aspects of changing costs and benefits of cleaner air, and how these changes affect welfare. A well designed policy depends critically to the extend that the benefit exceed the cost and how it compares to any other policy alternatives. Here I discuss two very different context, the cost of renewable energy in developed countries, and the benefits of switching to cleaner fuel in developing countries. This work aim to better inform policy makers about the alternative policies and its associated cost and benefit. I find that having fuel switching policy is welfare improving. Similarly having dynamic pricing is always welfare improving compared to flat pricing.

Chapter 2 studies the impact of a household fuel conversion program on infant mortality by examining a kerosene to liquid petroleum gas (LPG) conversion program, one of the largest household energy transition projects ever attempted in the developing world. In 2007, the government of Indonesia introduced this transition program to encourage more than 50 million households to switching from kerosene to Liquid Petroleum gas (LPG). Burning dirty fuel such as kerosene is the leading source of indoor air pollution and can be more severe compared to outdoor air pollution as the exposure is much greater and the fact that most people spend their time indoor. Based on exposure measurement studies, LPG produces significantly less indoor air pollutants compare to kerosene. I find a reduction in infant mortality and lower probability of being born with very low birth weight, with effects considerably larger for households where cooking is done indoors. This results suggest the importance of cleaner fuel interventions. Even a little improvement of indoor air pollution, a switch from kerosene to LPG, can lead to a reduction in mortality. A larger improvement in indoor air pollution (i.e. switching away from wood fuel to LPG) might save even more.

Chapter 3 examines the extent to which variable pricing can make renewable energy more cost effective in the state of Hawaii. Technological progress has lowered the cost of wind and solar power to make them competitive with coal and natural gas on a levelized basis. The problem having more renewable energy is the intermitency, which makes the supply side a lot more inelastic. One solution to intermittency is real-time retail pricing that reflects the incremental cost and marginal willingness to pay for electricity. This pricing scheme would create powerful incentives to efficiently store energy on a distributed basis or otherwise shift consumption from times and places of relatively scarce renewable supply to times and places of plenty. Electricity consumers already have access to many low-cost appliances and devices that store energy in different forms. By carefully timing water heating, electric vehicle charging and water pumping, using ice storage for cooling systems, making micro-adjustments for some kinds of refrigeration, or other means, electricity use can be shifted from seconds to many hours at low cost. Such mechanisms would need to be automated by smart devices acting on customers' behalf. These technologies can make electricity demand highly substitutable over time, at least over horizons up to a day or so. In addition to shifting the timing of electricity consumption within the day, customers facing dynamic prices can also adjust the total amount of power they consume each day, reducing total consumption during extended periods when power is scarce, or increasing it when power is abundant. Hawaii has a natural advantage in adoption of large shares of renewable energy, with plentiful renewable resources and expensive conventional generation. However, the intermittency challenge is especially acute in Hawaii, due to the states geographic concentration. This chapter shows that variable pricing provides little social benefit when we have less renewable energy, but it provides significantly more as the renewable share increases.

Chapter 4 investigates on the extent to which the switching improves households well-being. Burning dirty cooking fuels produces harmful air pollutants and has long been associated with poor health and low productivity. Policies that aim to improve modern energy access, including the seventh United Nation's Sustainable Development Goal, have been moving slowly, leaving half of the world population without access to clean cooking fuel. The desirability to switch to a cleaner fuel depends critically on the extent to which the switching improves households well-being. Using a nationwide transition from kerosene to cleaner burning propane in Indonesia, the same program as in chapter 2, I investigate households response to fuel switching. Based on combustion efficiency and end-use energy equivalence, LPG is cleaner and more efficient than kerosene. Using variation in the timing of the implementation on four waves of the Indonesia longitudinal survey, I compare changes in expenditure within households in the treated districts with changes in expenditure within households in not-yet treated districts. I find that households reduce their kerosene consumption up to 100% and their fuel expenses are reduced by 40%, or 1.19 USD per month on average. These effects are higher among poor households. I do not find any response to other nondurable expenditures which provides some evidence of consumption smoothing. This is as expected considering the size of the effect is only about a 2% reduction from total monthly expenditure. As fuel demand is inelastic, a small cost saving might indicate big welfare improvement. Adding to the literature of the benefit of switching to a cleaner fuel, the overall impact of this on-going fuel switching intervention can be enormous.

Chapter 2

Cooking Fuel and Early Life Health: Lesson from Indonesia

2.1 Introduction

In most developing countries, cooking fuels emit indoor air pollutants that may lead to poor health. The World Health Organization claims that dirty cooking fuels are associated with approximately 4.3 million premature deaths each year and pose health risks comparable to the hazards of smoking tobacco (WHO, 2016). But the magnitude of this correlation varies widely across studies, and a causal link has not been clearly established (Jeuland et al., 2015). Household behavior, among other factors, obscures health impacts. For example, the largest randomized control trial found no effect from free use of new, cleaner cooking stoves, because households used them irregularly and inappropriately (Hanna et al., 2016). People may also take actions to avoid inhaling smoke or particulate matter, especially when the pollutants are obvious and cause discomfort. In cross-sectional studies, risks of alternative fuels and cooking stoves can be confounded by the use of multiple fuels, not all of which may be reported, plus many unobserved factors that may be associated with cooking choices (Duflo et al., 2008).

In this paper, I evaluate whether cleaner cooking fuel affects health outcomes, focusing mainly on infant mortality. The study provides quasi-experimental evidence on the health benefits of switching to a cleaner cooking fuel, leveraging what may be the largest kerosene to liquid petroleum gas conversion program ever attempted in a developing country. The Indonesian government determined the location and timing of program implementation based on each regions' kerosene usage and its infrastructure readiness. Then, the government redirected kerosene subsidy budgets to LPG, a more efficient and cleaner fuel compared to kerosene[1]. This program, motivated mainly by a rising governmental cost of subsidizing kerosene, successfully reduced household use of kerosene by 83% in just 4 years.

I use three rounds of Indonesian Demographic and Health Surveys (2002, 2007 and 2012) and compare changes in infant mortality in the targeted districts to changes in infant mortality in untargeted districts. The identification strategy assumes that timing of program implementation is uncorrelated with other changes after 2008, conditional on district fixed effects, cohort fixed effects and household level controls.

The main threat to causal identification is that timing of program implementation might have been associated with unobserved factors that otherwise influenced infant mortality in the targeted regions. To address this threat, first, I show that similar pre-implementation trends in infant mortality existed in both targeted and untargeted districts. Second, I show that implementation timing has no association with trends in birth rates or household characteristics. These results offer reassurance that untargeted regions serve as a valid counterfactual. I further examine the results' robustness by using different specifications such as household fixed effects, coarsened exact matching (Blackwell et al., 2009), and propensity score matching (Rosenbaum and Rubin, 1983). I also test for the sensitivity of the results to including trends in household level controls, trends in regional and provincial level for local policy changes, as well as several placebo treatments.

[1]It is widely known that LPG produces significantly less $PM_{2.5}$ than kerosene because of higher combustion efficiency and $PM_{2.5}$ exhibits higher toxicity per unit mass than larger particulates (i.e. PM5 and PM10) (Peters et al., 1997; Smith et al., 2005).

I find that the program led to an increase in LPG use in place of kerosene and had no effect on the use of wood fuel. Four fewer infants died per 10,000 live births – a 1.1 percentage points reduction in infant mortality rate – than would have in the absence of the program. Approximately 600 infants were saved per year from 86 million kerosene users in the targeted regions. In the developing world, one billion kerosene users switching to LPG can save about 7,000 infants per year.

To also explore the mechanisms underlying these impacts on health, I look separately at the effects before and after birth. I consider pre-birth effects using the incidence of stillbirth, preterm birth and low birth weight as the outcome variables. I find that a reduction in the fetus exposure to the kerosene pollutants leads to a significant decrease in low birth weight that is not due to shorter gestation. I then consider effects of kerosene exposure after birth by estimating impacts infant and neonatal mortality conditional on birth weight and prenatal visits. I find the effect on infant mortality is driven mainly by fewer deaths during the first seven days after birth, which combined with the pre-birth effects, suggests that fetal exposure during pregnancy is the main mechanism.

I then consider accumulated effects from reduced kerosene exposure. Long-term exposure to kerosene has been associated with persistent damage to the pulmonary system (Ritchie et al., 2003). In line with this literature, I find that households that switched to LPG earlier experienced a larger reduction in infant mortality. This result could be driven by earlier adopters having higher incomes. Hence, I further test if low-socioeconomic households benefited more by the reduction in kerosene exposure. Poorer households may be less able to avoid exposure and/or less knowledgeable about potential health effects. I find that the reduction in infant mortality is stronger in infants living in rural areas and infants from low educated mothers. It is also stronger for households who cook inside the house as the health risk of burning dirty fuel is higher when the air circulation is poor.

This study adds a rare and thus valuable evidence on the effect of indoor air pollution on infant mortality in the developing countries literature[2]. Globally, approximately one billion people rely on kerosene and other polluting devices for lighting (WHO, 2016) and 500 million households use it for cooking (Lam et al., 2012). Adding to Barron and Torero (2017) which provides the first experimental evidence of a reduction in the kerosene usage leading to a lower acute respiratory infection among young children, I provide the first quasi-experimental evidence of a reduction in kerosene usage to infant mortality. Links with infant mortality are more plausibly causal because infants spend most of their time indoor, and have low migration rates, and are not subjected to the accumulated effect from unknown lifetime exposure to pollution (Chay and Greenstone, 2003). I can also hypothesize that switching from solid fuel, which is dirtier than kerosene, to LPG may bring even greater health benefits. This study suggests that policy interventions on subsidizing cleaner cooking fuel is one way to achieve the United Nations' Millennium Development Goals.

The rest of the paper is organized as follows: section 2 provides some background about cooking fuels and associated indoor air pollution in developing countries, program details and previous literature on kerosene and health; section 3 provides research design and data details; section 4 shows the results and robustness checks; section 5 discusses policy implication; and section 6 concludes.

2.2 Policy context of clean energy access

The seventh Sustainable Development Goal calls for universal access to affordable, reliable, sustainable and modern energy by 2030. In 2009, 1.3 billion people lack access to electricity (Barron and Torero, 2017) and, in 2010, 41 percent of households worldwide relied on dirty fuel for cooking (Bonjour et al., 2013). Interventions in clean energy need to be scaled up significantly to support this agenda. There are at least two common clean energy interventions to reduce indoor exposure to pollutants from burning dirty fuel: providing access to cleaner fuels

[2] The link between $PM_{2.5}$ from outdoor air pollution and infants' health in developed countries has been well documented (see Currie et al. (2009)).

and providing access to improved stoves. Investment costs and sustainability are among important considerations.

For the impoverished, kerosene is an expensive fuel (Trollinger, 2016). In mostly developing countries, it has been highly subsidized with $18 billion total subsidies per year (Mills, 2017). Globally, approximately one billion people rely on kerosene and other polluting devices for lighting (WHO, 2016) and 500 million households use it for cooking (Lam et al., 2012). For the first time, WHO re-classified kerosene as a dirty fuel, within the same category for biomass and coal (WHO, 2016). The link between kerosene use and health become increasingly important. In a response, interventions to replace kerosene with cleaner fuel such as LPG has been increasingly popular in North Africa, Mexico, Peru, El Salvador, Brazil, India, China, Malaysia, Thailand, and, among others, Indonesia(Pachauri et al., 2012; Toft et al., 2016).

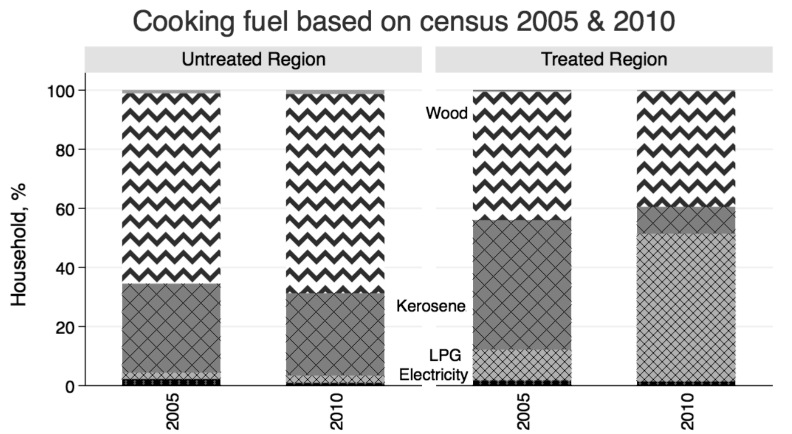
Indonesia's kerosene to LPG program, a unique policy intervention in household conversion, combines price subsidy and quantity restriction in the intervention. The switching to LPG is 'involuntary' in nature because the subsidized kerosene is removed from the targeted regions after LPG distribution. Mainly motivated to reduce the kerosene subsidy[3] , this conversion led to a reduction in 8.7 billion litres of subsidized kerosene or approximately 83% from total subsidized kerosene in 2007. From the census data, within only three years, the percentage of households who use *primarily* kerosene dropped significantly from 42% to 12%, and the percentage of households who use primarily LPG sharply increased from 9% to 46% (Figure 2.1).

2.2.1 Fuel Conversion Program in Indonesia

There was a need to rush in reducing the kerosene subsidy which took half of the government's oil budget. Hence, the May 2007 kerosene to LPG Program commenced after only 8 months of simple feasibility study and one-month of

[3]Indonesian government acknowledged other benefits from this program such as efficiency and environmental benefit.

Figure 2.1: Households' cooking fuel choice before and after the program



Notes: This figure shows the percentage of household based on their primary cooking fuel in targeted and untargeted regions before the program (2005) and after the program (2010). The proportion of household who use kerosene decreased from 42% to 12%; LPG – increased from 9% to 46%, wood – slightly decreased from 46% to 40%. Electricity has very small portion of users. Source: Indonesian census 2005 & 2010.

market trial. The program plan has continuously improved after the official Presidential Decree released on December 2007[4]. Since most regions that have access to kerosene are mostly electrified, kerosene is used by households mainly for cooking rather than lighting. Before the program started, kerosene was highly subsidized, on average, 62% of the market price, approximately \$0.41 per litre while LPG was not yet subsidized and priced at \$ 0.77 per kg in 2007[5]. After the program, LPG is available in 3 kg size with the subsidized price of \$0.42 per kg[6]. By adjusting the energy expenditures with price-to-kWh conversion factor and the fuel efficiency factor, Andadari et al. (2014) shows that the program was effective in reducing the percentage of people living under the lowest energy-poverty line but failed to substantially reduce the overall number of energy-poor people[7].

[4] `http://prokum.esdm.go.id/perpres/2007/perpres_104_2007.pdf`

[5] 1 litre kerosene $\approx$ 0.4 kg LPG (Budya and Arofat, 2011)

[6] Details of the program can be read in Budya and Arofat (2011).

[7] The study is based on a survey on 550 households in five subdistricts in Central Java in January 2010.

The Ministry of Energy and Mineral Resources selects the treated districts in a given fiscal year based on each district's level of kerosene usage, LPG infrastructure readiness, location and size of the area. Pertamina (Indonesia's national oil company) acts as the sole executor for the conversion program. The program was aimed to convert 73% of households[8], targeting households that use kerosene. Only eligible households[9] received one initial free LPG package (one LPG canister, a single LPG stove, hose and regulator) and allowed to refill the canister under the subsidized price. Table 2.1 shows that by 2008, the package had been distributed to 84 districts, mainly big cities in Java. By 2011, the program has reached out to now include 169 districts (out of 354). Figure 2.2 shows the program roll-out during 2007-2011. The colored area represents treated districts and the year in which the free LPG package was distributed while the white area represents the untreated regions. Initially, these untreated regions, mainly eastern Indonesia, were completely excluded due to infrastructure unreadiness and high transportation costs but recently they are being considered to be included in the future.

Table 2.1: Number of districts based on program roll-out

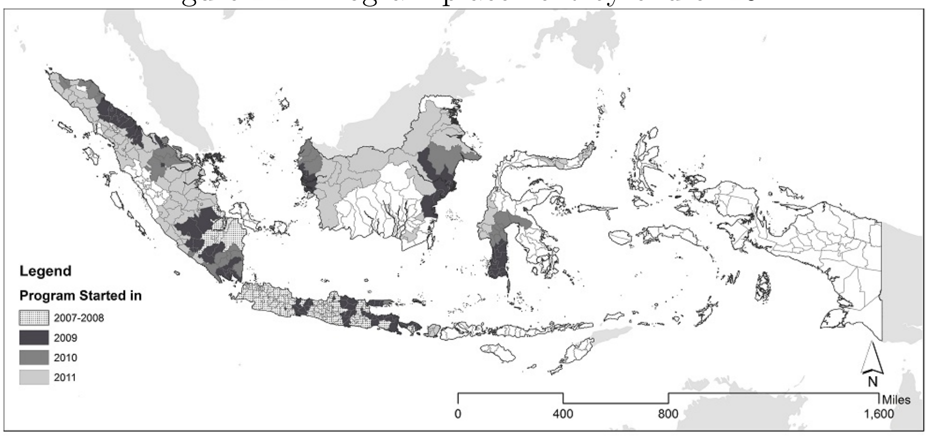
Regions	Program year						Total districts
	0	2007	2008	2009	2010	2011	
Sumatera	24	1	4	24	15	35	103
Java	0	22	59	32	1	0	114
Bali and Nusa Tenggara	17	1	3	5	0	4	30
Kalimantan	15	0	0	7	4	13	39
Sulawesi	17	0	0	15	6	8	46
Maluku and Papua	22	0	0	0	0	0	22
Total	95	24	66	83	26	60	354

Figure 2.2.1 shows the supply quantity of subsidized kerosene relative to base year (base year for kerosene is 2006 while base year for LPG is 2012). Kerosene supply decreased and LPG supply increased gradually starting from January 2008. During 2007-2008, Pertamina faced serious field challenges such as strong resistance from the community (mass protests and negative public opinion in

[8] 42 millions from 57 million total households in 2007

[9] Eligible households are households who have been using kerosene and have never use LPG before. There is a third-party surveyor assigned to do the collect data from eligible households.

Figure 2.2: Program placement by end of 2011



Notes: by 2008, the free initial LPG packages were distributed in mainly Java, and Bali. By 2011, they were distributed in some part in Sumatera, Nusa Tenggara, Kalimantan, and Sulawesi. White coloured regions has not yet distributed after 2011. Source: constructed by author based on LPG realization data from Pertamina

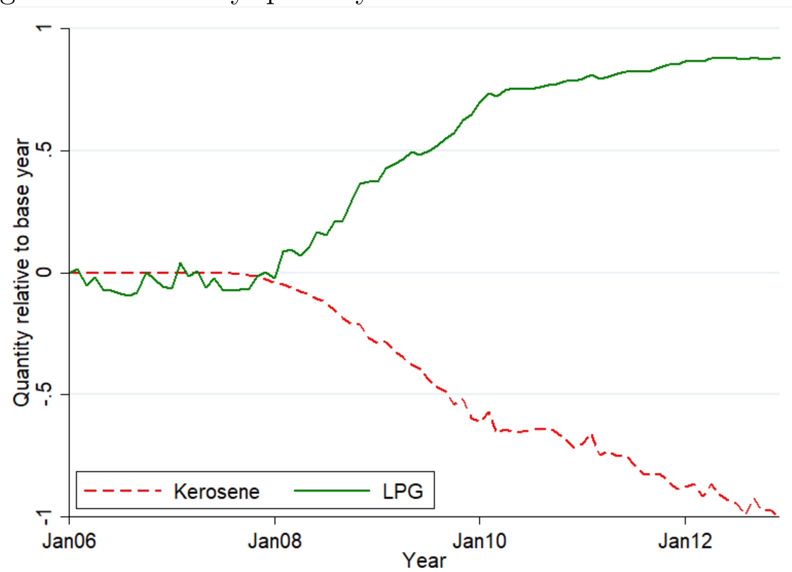
the media[10]) and a simultaneous kerosene and LPG scarcity which then led to a significant rise in both kerosene and LPG prices[11]. During the price spike, some households used multiple fuels, including wood, to fulfill their daily energy needs (Hasanudin et al., 2011; Andadari et al., 2014).

2.2.2 Potential impact of kerosene usage on productivity and health

Literature has mainly focused on the adverse health risks from burning solid fuels rather than kerosene since solid fuel pollutants are obvious and cause greater discomfort. Although kerosene smoke is less visible, burning kerosene shows similar adverse health risk to those of solid fuels' (Pokhrel et al., 2010; Lam et al., 2012). Compared to LPG, kerosene produces significantly more fine particles ($PM_{2.5}$) due to lower combustion efficiency (Smith et al., 2005). In particular, it emits a very high level of black carbon, a chemical speciation of $PM_{2.5}$, which is associat-

[10]There were also many accidents involving LPG explosions being reported in the media
[11]The kerosene scarcity led to severe inflation (Budya and Arofat, 2011)

Figure 2.3: Monthly quantity of subsidized kerosene and LPG



Notes: Supply of subsidized kerosene is relative to 2006 quantity. Supply of subsidized LPG is relative to 2012 quantity. Source: Pertamina.

ed with lung cancer, and cardiovascular mortality, morbidity, and likely adverse birth and nervous system effectsWHO et al. (2012); Grahame et al. (2014).

Combustion products from burning kerosene have been indicated as potential mutagens and carcinogens. They are also capable of interfering with the development of an embryo fetus (Maiyoh et al., 2015). In a group of children with cancer, exposure to kerosene stoves on pregnant mothers is highly associated with occurrence of brain tumors in young children (Bunin et al., 1994). Carcinogenic effects of particulates from benzene, one of the combustion products from burning kerosene, has been found to increase incidence of acute non-lymphocytic leukaemia (Duarte-Davidson et al., 2001). Toxicants such as n-Hexane, naphthalenes, and polycyclic aromatic hydrocarbons (PAH) from burning kerosene were also found to have neurotoxicity effects (Ritchie et al., 2003), which are likely to reduce postnatal growth.

Cooking with kerosene has particularly different behavioral responses. Households who use kerosene are more likely to cook indoors, to cook for longer durations, and to cook closer to the stoves compared to when they use solid fuels. This is because kerosene burns more cleanly compared to solid fuels and produces significantly less amount of smoke (Saksena et al., 2003). Moreover, some Randomized Control Trials (RCT) find that when cooking is more comfortable with cleaner fuels or cleaner cooking stoves, households are likely to cook more food and more frequently (Burwen and Levine, 2012; Hanna and Oliva, 2015). Hence, when their fuel consumption increases, it is unclear whether their exposure to indoor air pollutant decreases. Even less is known about household's energy mix and the factors that motivate the households to adopt them. For this reason, RCT, which focus on the effectiveness of existing interventions under tightly controlled conditions, may not provide the most useful information for large-scale interventions.

To what extent does burning kerosene lead to infant deaths has not yet clearly established. Association between kerosene usage and health outcomes from cross-sectional studies does very little in explaining the magnitude of the relationship. RCT studies do not find any health improvement from cleaner cooking stove interventions because households do not use the stoves consistently and properly Hanna et al. (2016). One main drawback in providing cleaner cooking stoves is the non-compliance issue. Households can revert back to using the old stoves (Burwen and Levine, 2012). Households also choose their cooking fuels based on the most economically available fuels, despite of any additional cash incentives given to encourage cleaner fuels usage (Hanna and Oliva, 2015).

This study, however, has an important feature of 'involuntary' fuel switching induced by the kerosene subsidy removal. The program design does minimize the rate of non-compliance, anecdotally. The study makes it more likely to document the link between kerosene usage and infant mortality. Although the issue of non-compliance still exists, like in any other intervention, it is important that this study incorporates such behavioral responses in the estimation.

2.3 Research Design

Common cross-sectional analysis does not fully address the potential confounder due to the non-randomness of fuel choice. To address this, I use a quasi-experimental approach, exploiting the sharp variation of fuel choice induced by the fuel conversion program to rule out the endogeneity bias. The main objective is to estimate the causal effect of the program on infant mortality. In pollution and health literature, to avoid the 'curse of dimensionality', I assume that covariates are linear and additive, following Chay and Greenstone (2003). I use difference-in-differences (DID) estimation strategy and compare within district and birth year average infant mortality rate between targeted and untargeted regions, following below equation:

$$y_{irt} = c + \alpha_r + \beta_t + \theta Treatment_{rt} + \tau X_{irt} + \epsilon_{irt} \tag{2.1}$$

where y_{irt} be the outcome variable for infant i in region r at time t which takes the value of 1 if the infant died and 0 otherwise. α_r and β_t are district and year of birth fixed effects to control for permanent unobserved differences across districts and cohorts. X_{irt} is a set of covariates that capture birth, parental and household characteristics. ϵ_{irt} is the error term. $Treatment_{rt}$ is a dummy indicating the program status in district r in year t. The average treatment effect is captured by the θ coefficient.

Even though the outcome variable is binary, I use the linear probability model for the ease of interpretation. One drawback of using the linear probability model is that the estimated coefficients can imply probabilities outside the unit interval [0,1]. Since the main interest is to estimate the partial effect of the program to the infant mortality rate, averaged across the distribution of the program, then the fact that some predicted values are outside the unit interval may not be very important (Wooldridge, 2010). On the other hand, with fixed effects probit models, one needs to make arbitrary assumptions on the value of fixed effects to calculate marginal effects of the independent variables. For the robustness, conditional probit estimation confirms that the signs and significance of the relevant coefficients hold.

Ideally, births should be matched to the district, month and year of the program implementation. But the data on the program implementation does not have this level of timing detail. In addition, the actual fuel switching is influenced by the timing of initial LPG distribution and the subsequent timing of subsidized kerosene withdrawal which could be varied in the actual implementation. Hence, I explore two approaches. First, I assume the LPG distribution was spread equally throughout the year; then I match births that occurred in the second half of the implementation year as the treatment group[12]. Second, I exclude the first year of the program implementation; then I match births that occurred in the subsequent year as the treatment group. As the results are very similar (see Section 2.4.5), I use the first approach to present the main result to maintain the sample size.

Following the WHO definition, infant mortality rate is defined as the number of deaths of children under one year of age. Infants are one of the main interests of policy makers as the economic loss from future outcomes might be larger than those of adults (Currie et al., 2009). Moreover, infant mortality rate has been indicated as a superior measurement in the air pollution literature compared to the other alternatives such as adults' health or children's health. In fact, the exposure level from household air pollution is highly varied and its lifetime accumulated impact is unknown. Infants not only spend most of their time indoors, are particularly more vulnerable to environmental risk, and have relatively low migration rates, but also have not yet been exposed to an unknown lifetime of pollution compared to adults (Chay and Greenstone, 2003). Hence, using infant mortality rate as an outcome variable is helpful for identification purposes. In the main analysis, I also explore if there is a disproportionate impact on fetuses and new borns, later called perinatal mortality[13].

[12] I tried different monthly births cut-off ranges that occurred in February to October, and the results are insensitive to this cut off. The effect does look more precise starting with the third month (see Appendix A)

[13] Perinatal mortality is defined as the number of stillbirths and deaths in the first week of life.

The program status in this research design identifies the impact of the program on the individual outcomes in the particular sample used in the regression. It is noteworthy that the data is not informative about the precise fuel mix and the exact time of fuel switching. Fuel stacking (e.g. when households used both kerosene and wood but reported wood as their primary cooking fuel) is a common practice. In response, my estimation in this study is equivalent to the *intent-to-treat* (ITT) effect. If fuel choice induced by the program is uncorrelated to expected birth outcomes, the magnitude of all estimates would have to be multiplied by one over the share of targeted population in order to get to an average treatment effect (ATE). [14]

2.3.1 Data and Variables

2.3.1.1 Demographic and Health Survey

For health outcomes, I use three rounds of the Indonesian Demographic and Health Surveys (IDHS) (2002, 2007, 2012). IDHS 2007 and 2012 include all provinces (33 regions and 354 districts) whereas IDHS 2002 excludes 4 regions: Nanggroe Aceh Darussalom, Maluku, North Maluku, and Papua due to unstable political situation. Census blocks in urban and rural areas were selected using multistage-stratified sampling for each province. The response rates for both household and individual interviews were 99% on average. Women who have ever been married (15-49 years old) and household heads were asked about all birth information within five years preceding the survey, as well as maternal and household characteristics. DHS has information for all births within the household. I use this to check for robustness in section 2.4.5. Since pregnancy-related variables are recorded only for children born within the last five years, the main analysis is limited to range in order to have a comparable sample size

[14]ITT gives a pragmatic estimate of the benefit of the policy rather than the actual measurement of fuel switching. The prevalence in ITT analysis is that it accounts for non-compliance and fuel stacking. Fuel stacking is a common issue in survey-based studies in other countries since survey data only captures household *primary* cooking fuel.

between models with different control variables. Sampling weights provided in the survey are not used in the main regression since I focus on estimating the relationships at the individual level.

I define infant mortality as the death within one year to account for heaping (see Figure B.2 in Appendix)[15]. Common reporting issues include recall error and survivor bias. First, recall error happens when respondents were more likely to forget distant child births or underreported births when they did not want to talk about the death of their child. Generally, this problem is less serious for recent births rather than more distant births. This recall error of births might lead to attenuation bias, in which case made my estimates a lower bound. To minimize this problem, I also include dummies for recall period, following Ngandu et al. (2016). Second, survival bias happens when the survey is limited to only surviving women at age 15-49. In the case of Indonesia, the survival bias is likely to be negligible (Indonesia, 2012). But if the fertility of surviving and non-surviving women differs substantially, and given that no data is available for children of women who had died, also makes my estimates serve as a lower bound.

The base regression includes dummies for birth order, recall period, and singleton and multiple birth. Following the literature and considering non-missing values to maintain a comparable sample size, the set of control variables includes dummies for mother's and spouse's education, mother's age at birth, a dummy for young mothers (i.e. mothers younger than 18 years old), parents' smoking behaviour, parents' visits to the health facility in the last 12 months, safe drinking water sources (i.e. water from protected wells, water pipe built inside the dwellings, bottled water or filtered water), availability of private toilets, electrifications, ownership of fridge and TV, and a dummy for the firstborns .

The empirical analysis focuses on comparing changes in birth outcomes within targeted and untargeted regions after 2008 with the total sample of 39,348 observations. I exclude 12,133 births between 2007-2008 because of two reasons.

[15]Technical definition of infant mortality is the death happen less than one year but the heaping of deaths at age 1 month and 12 months are common in the survey.

First, starting from 2009, the program was operated smoothly without major operational issues (Budya and Arofat, 2011). Before that, during 2007-2008 the program has significant operational problems as discussed in Section 2.2.1. Moreover, during 2007-2008, the program also heavily targeted big cities, densely populated regions with a high level of kerosene consumption. Excluding these regions helps to exclude the 'unintended consequences' from those operational problems and improves the comparability between targeted and untargeted regions. Second, this selected sample excludes the period of financial crisis that happened between 2007-2008.

Overall, the treatment group after 2008 is more similar to the control group in many observed characteristics[16]. I acknowledge that DID estimation only assumes that the infant mortality in targeted regions will have similar trends with the untargeted regions in the absence of the program, regardless of their initial characteristics. In fact, the previous study on the impact of financial crisis in Indonesia indicates that regions were affected differently based on regions' characteristics (Levinsohn et al., 2003). It is therefore useful, in this case, to compare treatment and control groups that have similarity both in initial characteristics and trends as they are likely to be effected equally by the crisis. Finally, I also add the robustness checks that include all the sample (including previously excluded regions) in Section 2.4.5. I show that the inclusion of the excluded groups gives similar results but larger standard errors.

Supplemental data for district variations are taken from Indonesia Database for Policy and Economic Research (INDO-DAPOER)[17], an integrated panel dataset of infrastructure, fiscal, economic, social and demographic at district level collected by The World Bank though many sources. District level variables mainly come from PODES, a census of all villages and towns in Indonesia. Matching the district variable to the main data set is challenge as the district data is limited on certain year of survey. In 52 million LPG packages were distributed and 64% of it

[16]The comparison between targeted and untargeted districts is provided in the Appendix Table A.1 (for district characteristics) and Table A.2 (for household characteristics).

[17]https://data.worldbank.org/data-catalog/indonesia-database-for-policy-and-economic-research

was distributed in 2009-2011 to 163 districts. From a separate trend analysis on district variation overtime, there is very small variation in district characteristics before and after the program (see Appendix A.1) thus the analysis is focused on using district fixed effects that will account for any permanent difference between districts.

2.3.2 Validity of the empirical strategy

I assume that the program status is not correlated with other changes after the program, conditional on district and year of birth fixed effects, and household level controls. The targeted regions and the timing of the program are determined by the Ministry of Energy and Mineral Resources independently from any other major national programs (discussed in Section 2.2.1). The remaining concern, however, is if (1) there is a systematic difference in the pre-existing trend in infant mortality, and/or (2) there is a correlation between the program status and any other factors that also correlated with infant mortality after the program. If these two hypotheses cannot be rejected, then the assumption may not be valid. I test these two hypotheses in following sections.

2.3.2.1 Similarity in pre-implementation trends

First, using only 2002 and 2007 survey, I present average household characteristics at the baseline years from the regression equation below:

$$z_{irt} = c + \alpha_r + \beta_0 S_{2007} + \gamma_0 T_r + \theta_0 S_{2007} * T_r + \epsilon_{irt} \tag{2.2}$$

where S_{2007} is an indicator for 2007 survey and T_r is an indicator for targeted districts. Table 2.2 column 1 reports average characteristics for households in the untargeted districts (i.e. control group). Column 2 reports average characteristics of households in the targeted districts (i.e. treatment group). Column 3 reports the within-district mean differences between households in columns 1 and 2 (γ_0). Column 4 reports within-district trends between households in columns 1 and 2 (θ_0). The table shows 40% (34 million people) used kerosene as their primary cooking fuel and 10% (8 million people) already used LPG. Within districts, there is no significant change during 2002 and 2007.

Across districts, households in the targeted districts are more educated and economically better (e.g., they are more likely to own TV, fridge, private toilet, and electricity). The initial number of children born in the last five years preceding each survey year is higher for the targeted districts than the untargeted, but there is no difference in the trend. At 10% significance level, children in the targeted regions were more likely to be born with low weights. The coefficient of the number of antenatal visits in column (4) indicates less antenatal visits in the targeted districts. In fact, this negative coefficient is due to an upward trend in antenatal visits in the untargeted districts which might be because of the gradual improvements in the regional infrastructure overtime[18]. Overall, within district differences, households in the targeted districts generally are similar both in initial characteristics and trends.

Figure 2.4 shows the mean of infant mortality rate for the treated and untreated groups. The x-axis indicates the year of birth. Vertical dash line shows the beginning of 2009 which is the start of the program implementation. Infant mortality rate in both groups show a similar downward pre-trend. Note that year-to-year trends are subjected to a considerable amount of noise. The 2012 survey ended in the July of 2012 thus only has six months of birth records.

2.3.2.2 Correlation with other characteristics

Second, using all sample, I test if the program correlates with other households' observable characteristics following below Eq. 2.3. Each row in Table 2.3 reports a within district regression on each corresponding dependent variable. There are no noticeable differential change over time in birth and household characteristics except the proportion of non-smoker is increased about 1 percent at the 10%

[18]Note that antenatal visits are only recorded for the latest child born in the survey.

Table 2.2: Baseline characteristics between treatment and control group

	Mean				Within-district			
	Control group (1)		Treatment group (2)		Level differences (3)		Trend differences (4)	
Total observations	11,195		14,667					
Cooking fuel choice								
LPG	0.06	(0.23)	0.30	(0.46)	0.07	(0.08)	0.00	(0.01)
Kerosene	0.27	(0.44)	0.31	(0.46)	-0.05	(0.04)	-0.01	(0.02)
Wood	0.67	(0.47)	0.39	(0.49)	-0.02	(0.04)	0.02	(0.02)
Birth outcomes								
Infant death	0.04	(0.20)	0.03	(0.17)	0.01	(0.01)	0.00	(0.01)
Perinatal death	0.02	(0.15)	0.02	(0.13)	0.01*	(0.01)	0.00	(0.01)
Low weight (¡2500 g)	3.16	(0.62)	3.17	(0.56)	0.04	(0.05)	0.02*	(0.02)
Birth weight (in kilogram)	0.15	(0.36)	0.12	(0.33)	-0.11*	(0.06)	0.00	(0.03)
Birth characteristics								
Antenatal visits	6.16	(3.76)	7.63	(3.70)	-0.68	(0.61)	-0.48**	(0.23)
Age at birth	27.77	(6.43)	27.70	(6.30)	-0.08	(0.71)	-0.05	(0.25)
Mother's age <19	0.05	(0.22)	0.05	(0.22)	0.02	(0.02)	0.01	(0.01)
First birth	0.30	(0.46)	0.37	(0.48)	0.02	(0.03)	0.01	(0.02)
Child born in the last 5 years	1.48	(0.63)	1.28	(0.50)	0.14**	(0.05)	-0.03	(0.03)
Household characteristics								
Number of household member	5.84	(2.42)	5.34	(2.03)	0.13	(0.23)	-0.07	(0.10)
Has TV	0.51	(0.50)	0.78	(0.42)	0.02	(0.05)	-0.03	(0.02)
Has fridge	0.21	(0.41)	0.31	(0.46)	0.12	(0.13)	0.01	(0.02)
Has clean water for drinking	0.21	(0.41)	0.37	(0.48)	0.26	(0.20)	0.03	(0.03)
Visited health facility last 12 months	0.51	(0.50)	0.53	(0.50)	-0.18	(0.12)	0.03	(0.04)
Do not smoke	0.98	(0.15)	0.99	(0.12)	-0.01	(0.00)	0.00	(0.00)
Do not have own toilet	0.66	(0.47)	0.48	(0.50)	-0.06	(0.06)	0.01	(0.03)
Has electricity	0.73	(0.45)	0.94	(0.23)	0.03	(0.08)	-0.02	(0.03)
Parents' education								
Mother: secondary and higher	0.45	(0.50)	0.41	(0.49)	0.00	(0.04)	-0.01	(0.02)
Spouse: secondary and higher	0.55	(0.50)	0.59	(0.49)	0.04	(0.05)	-0.03	(0.02)

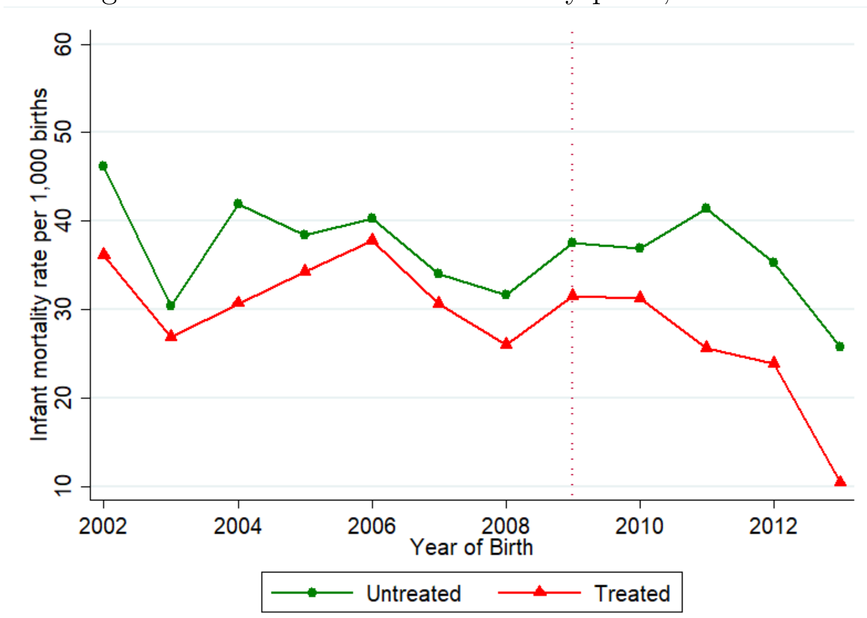
Notes: Column 1 reports average characteristics for household in the control group: untreated districts. Column 2 reports average characteristics of household in the treatment group: treated districts. Column 3 reports the within-district mean differences between households in column 1 and 2 (γ_0 in Eq. 2.2). Column 4 reports within-district trends between households in column 1 and 2 (θ_0 in Eq. 2.2). All regressions include district fixed effects. ^{a} Antenatal visits variable is recorded for the latest birth thus have a smaller sample. Standard errors in parentheses are clustered at the district level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

significance level.

$$z_{irt} = c + \alpha_r + \beta_1 S_{2012} + \gamma_1 T_r + \theta_1 S_{2012} * T_r + \epsilon_{irt} \tag{2.3}$$

The results in both Table 2.2 and Table 2.3 provide support that the program does not lead to any differential change other than to infant mortality. In other words, the untargeted districts are likely a valid counterfactual for the targeted districts in the absence of the program. Although there is no direct test of exogeneity that can be done, the absence of significant correlation with

Figure 2.4: Trend of Infant Mortality per 1,000 births



Notes: The figure plots the mean of infant mortality rate in treated districts and untreated districts after 2008. X-axis indicates the beginning of the year of birth. Vertical dash line shows the beginning 2009 which is the start of the program implementation. Note that year-to-year trend in mortality rates is subjected to a considerable amount of noise.

the main observable characteristics could suggest that there is neither significant correlation with unobservable variables (Tanaka, 2015).

2.4 Empirical Results

2.4.1 Impacts on Fuel Choices

Table 2.4 shows that the program, on average, led to a 10 percent decrease in the kerosene use, a 9 percent increase in the LPG use, and no effect on the wood use. This is unsurprising, given that wood users are not eligible for the program. It is possible that wood users may have illegally obtained subsidized LPG but the result in column (3) shows that this is not the case. Wood users likely do not have incentive to switch to LPG as wood fuel is the cheapest compared to all fuel alternatives and can be obtained with almost zero monetary cost.

Table 2.3: The effect on household characteristics

Dependent variables	Treated district X Program (θ_1) (1)		Treated district (β_1) (2)		Mean of dep. variable (3)	Observations (4)	R-squared (5)
Household characteristics							
Number of household member	-0.17	(0.12)	0.41*	(0.23)	5.41	39,348	0.08
Has TV	-0.02	(0.03)	0.07	(0.08)	0.69	39,305	0.23
Has fridge	0.02	(0.03)	0.06	(0.06)	0.29	39,226	0.19
Has clean water for drinking	0.02	(0.04)	0.14	(0.13)	0.32	39,338	0.24
Visited health facility last 12 months	0.01	(0.04)	-0.09	(0.09)	0.49	39,297	0.08
Do not smoke	0.01*	(0.01)	-0.02**	(0.01)	0.98	39,328	0.04
Do not have own toilet	-0.01	(0.03)	-0.01	(0.05)	0.54	39,294	0.17
Has electricity	-0.04	(0.03)	0.02	(0.08)	0.87	39,291	0.21
Parents' education							
Mother: secondary and higher	0.02	(0.02)	-0.01	(0.04)	0.58	39,346	0.12
Spouse: secondary and higher	0.01	(0.02)	-0.02	(0.04)	0.60	39,178	0.11

Notes: This table reports two regression coefficients from Eq. 2.3. Column 1 reports the coefficient of the program placement and Column 2 reports the coefficient of treated districts. All regressions include district and survey year fixed effects which were not shown to save space. Standard errors in parentheses are clustered at the district level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

2.4.2 Impacts on Birth Outcomes

This quasi-experimental setting does not use the main cooking fuel as a regressor which is endogenous and a major weakness in the earlier literature. Since I do not use the main cooking fuel variable, I am allowing the estimate to include fuel-stacking. Table 2.5 reports coefficient θ from Eq. 4.1. Outcome variables in column (1)-(4) is infant mortality (i.e. infant death within one year) and column (5)-(8) is perinatal mortality (i.e. stillbirths and infant death within one week). Column (1) is the most parsimonious model and uses only district and year of birth fixed effects. Column (2) adds a set of covariates as discussed in Section 2.3.1 to the model used in column (1). Column (3) adds the interaction of all covariates with dummy program to the model used in column (2) to absorb the differential trends in household characteristics. In column (4), I replace the birth year fixed effects used in the three earlier models with month-year of birth fixed effects.

Table 2.4: The effect on household's fuel choice

	LPG	Kerosene	Wood
	(1)	(2)	(3)
Treat	0.362***	-0.344***	-0.017
	(0.034)	(0.032)	(0.028)
Constant	0.104	0.372	0.511
	(0.074)	(0.065)	(0.037)
Mean	0.237	0.291	0.462
R-squared	0.329	0.225	0.283

Notes: This table explores the program effect on the types of fuel used for cooking. All regressions include district fixed effects. Standard errors in parentheses are clustered at the district level. Sample size: 39,348. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 2.5: Policy effect on infant and perinatal mortality

	Infant mortality (mean: 36 per 1,000 live births)				Perinatal mortality (mean: 18 per 1,000 live births)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment (θ)	-0.011***	-0.010**	-0.011***	-0.013***	-0.007**	-0.005*	-0.007**	-0.008**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)
Constant	0.001	0.020	0.216	0.167	-0.026***	-0.004	-0.042***	-0.028
	(0.028)	(0.031)	(0.219)	(0.218)	(0.006)	(0.009)	(0.014)	(0.017)
Observations	39,346	38,888	38,888	38,888	39,348	31,355	38,890	38,890
R-squared	0.044	0.048	0.053	0.058	0.033	0.019	0.038	0.043
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
ControlsXPost	No	No	Yes	Yes	No	No	Yes	Yes
Month-year FE	No	No	No	Yes	No	No	No	Yes

Notes: All regressions include district and year of birth fixed effects and report the θ coefficient from Eq. 4.1. Control variables included are discussed in section 2.3.1. ControlsXPost represents the interaction between all control variables with dummy program. Outcome variables in column (1)-(4) is infant mortality (i.e. infant death within one year) and column (5)-(8) is perinatal mortality (i.e. stillbirths and infant death within one week). Only treatment coefficient θ (in percentage points) is shown to conserve space. Standard errors (in parentheses) are clustered by district. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 2.5 shows that the program lead to 1.1 percentage points decrease in infant mortality or 4 infants per 10,000 live births. The program also lead to a 0.7 percentage points decrease in perinatal mortality at 5 percent significance level or 1.2 infants per 10,000 live births. The estimates are consistent across models and stronger with month-year fixed effects model (column (4)). Given that there are not many still birth incidents, the result is for perinatal mortality is mainly driven by early neonatal death which explain 30% of the infant death. The coefficients of other control variables (showed in Appendix Table A.3) are consistent with the broader literature. Highly educated mothers, electrification, access to clean water for drinking, non-smoking behavior, frequency in visiting health care in the last one year, all are significantly associated with a reduction to infant mortality. In line with the literature, young mothers have higher pregnancy risk which associated with higher infant mortality. The ownership of TV, fridge, age at birth, age of mother's at first birth, access to a private toilet and the spouse's education are not significantly associated with infant mortality.

This study is the first to estimate infant saved from a reduction in household air pollution. With a similar estimation strategy, Tanaka (2015) finds that the air regulation in China led to 3-6 six child per 1,000 births annually. Jayachandran (2009) find that outdoor air pollution from forest fires in Indonesia lead to 3.5 higher early-life mortality [19]. It places my estimates within the lowest range: 0.4 infants per 1,000 births to the outdoor air pollution literature. Note that this study captures the improvement of the indoor air pollution from kerosene to LPG which is potentially smaller than any air quality in these studies.

2.4.3 Potential Mechanism

2.4.3.1 Direct effect before and after birth

This section explores if fetals and infants exposure to kerosene pollutant is a possible mechanism that explains the reduction in infant mortality rate. As dis-

[19] The estimates is calculated from birth rate and population in year 2000

cussed in Section 2.2.2, exposure to kerosene stove during pregnancy could affect fetuses and infants through what often called biological mechanism. The hypothesis is that switching from kerosene to LPG might reduce indoor air pollution which then improve fetals development and infants' health after birth. Indoor air pollutants can only effect fetuses through their mother during pregnancy. On the other hand, the effect on infants can be an accumulated effects during gestation period and the effect on the exposure after birth. Following Currie et al. (2009), I estimate the effect of the program before and after birth. First, I estimate the effect on health before birth using stillbirths (i.e. fetal deaths in after seventh month of pregnancy), preterm births (i.e. premature births when the gestational age is less than eight months), and birth weights (i.e. in grams and in categorical) as the outcome variables. Second, I estimate the effect on infant mortality conditional on health at birth which is measured by birth weight.

Table 2.6 shows the effect of the program on health before birth in column (1) - (5) and after birth in column (6) - (7). Each of the column is a separate regression that include the base model, the set of control variables and its interaction with program dummy on the corresponding outcome variable in each column header. Before birth, the policy leads to a significant decrease in the probability of very low weight births (<1500 g) and low weight births (<2500 g). I find that the program has no effect on stillbirths, preterm births, and birth weight measured in grams. I also do not find any significant effects on the length of gestation[20] which mean that the effect on the probability of very low birth weight are not due to shorter gestation. Note that selection bias might lead to underestimation. For example, low weight infants from poor households are less likely to have their weight recorded due to poor delivery facilities[21]. If this is the case then my estimate serves as a lower bound.

[20] Result is available upon request

[21] In fact, 26% of births in the sample have missing value in their weight at birth.

Table 2.6: The program effect before and after birth

	Before birth					After birth	
	Stillbirth (1)	Preterm birth (2)	Weight (grams) (3)	Weight <1500 g (4)	Weight <2500 g (5)	Death w/in 1 yr (6)	Death w/in 7 days (7)
Treatment (θ)	0.000	0.004	0.001	-0.004*	-0.016*	-0.006*	-0.004**
	(0.001)	(0.007)	(0.016)	(0.002)	(0.009)	(0.003)	(0.002)
Constant	0.005	0.032	2.494***	0.008	1.013***	0.000	0.024
	(0.005)	(0.233)	(0.152)	(0.011)	(0.099)	(0.026)	(0.016)
Observations	31,355	31,355	23,896	23,896	23,896	23,896	23,896
R-squared	0.014	0.023	0.084	0.033	0.067	0.035	0.035
ControlsXPost	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth weight	No	No	No	No	No	Yes	Yes
Antenatal visitsXPost	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports the θ coefficient from Eq. 4.1 and shows the effect of the program on health before birth in column (1) - (5) and after birth in column (6) - (7). Each of the column is a separate regression that include the base model, the set of control variables and its interaction with program dummy on the corresponding outcome variable in each column header. In column (6) and (7), I add weight at birth as control variables flexibly using a continuous variable and a series of dummies for birth weight (<1500 g, 1500-2500 g, 2500-3500 g, and over 3500 g). Standard errors (in parentheses) are clustered by district. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

In column (6) and (7), I add weight at birth as control variables flexibly using a continuous variable and a series of dummies for birth weight (<1500 g, 1500-2500 g, 2500-3500 g, and over 3500 g). After birth, the policy reduces both infant mortality and early neonatal mortality, conditional on birth weight. Overall, the program has a much larger impact on mortality than on birth weight. The effects on infant mortality are mostly driven by the effect on neonatal mortality. This suggests that biological mechanism is a potential causal pathway linking fetals and the kerosene-related pollutant exposures.

2.4.3.2 Indirect effects

The program might affect infant's health through other channels other than through the pollutant exposure. Antenatal visits, mother's age at birth, birth order and total number of births are high likely to also influence infant mortality rarte. In this section, I test if the program affect these variables: the frequency of antenatal visits, mothers' age at birth, the first born, and the total number of births in the last five years.

Table 2.7 reports two regression coefficients from Eq. 2.3. Column 1 shows the coefficient of the program placement and Column 2 reports the coefficient of treated districts. Column (1) shows that mothers were paying less visits for antenatal care during pregnancy after the program. It might be that mothers no longer have many pregnancy-related problems as before the program which then lead to lower likelihood to seek antenatal care. In fact, Table 2.7 row (1) shows there is no differential changes in antenatal visits.

Table 2.7, row (2) shows that the program does not lead to a changes in mother's age at birth. Young mothers (age less than 19) have a higher risk in pregnancy compared to mothers older than 19 years old. If the program affects fertility and leads to changes in the the likelihood for young mothers to get pregnant, then the program effect on infant mortality might be driven by the changes in pregnancy risk in the sample composition. One other possibility of compositional issue is that if the program affects the probability of new mothers having their firstborn. Row (3) shows that the program does not lead to a changes in composition of young mothers. Row (4) shows that the program does not lead to changes in the probability of new mothers having their firstborn.

One possible source of bias is that if there is any differential trend fertility in the targeted districts. I test if the program lead to changes in number of children born in the last five years preceding the survey. Row (5) shows that the program does not effect the number of children born in the last five years. Furthermore, I aggregate number of child births at the district level then regress it with the district fixed effects, the program placement, survey year, and the interaction between program status and survey year[22]. If the coefficient on the interaction term between the program status and survey year 2012 is significant then it would indicate that the trends on number of birth in treated districts have a differential trend and the decrease in infant mortality can be driven by the changes in the number of births in the last five years preceding the survey. Total births is served as a proxy for fertility. The results confirm that the decrease in infant mortality is unlikely to be due to the differential change in fertility.

Table 2.7: The effect on other birth characteristics

Dependent variables	Treated district X Program (θ_1) (1)		Treated district (β_1) (2)		Mean of dep. variable (3)	Observations (4)	R-squared (5)
Antenatal visits[a]	-0.08	(0.25)	-0.58*	(0.32)	6.60	31,702	0.15
Age at birth	-0.07	(0.21)	0.54	(0.47)	27.56	39,348	0.03
Mother's age <19	0.01	(0.01)	0.00	(0.02)	0.05	39,348	0.02
First birth	0.02	(0.01)	-0.07**	(0.03)	0.34	39,348	0.02
Child born in the last 5 years	-0.02	(0.03)	0.07**	(0.03)	1.35	39,348	0.08

Notes: This table reports two regression coefficients from Eq. 2.3. Column 1 reports the coefficient of the program placement and Column 2 reports the coefficient of treated districts. All regressions include district and survey year fixed effects which were not shown to save space. [a]Sample for antenatal visits is slightly less as it is only recorded for the latest birth. Standard errors in parentheses are clustered at the district level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Another possibility is that the program changes the time allocation. I separately regress the indicator variables for employment and leisure time. Employment variable is measured in three dummy variables: employed all year, employed seasonal, employed occasional. Watching TV is used as a proxy for leisure time

[22]The result is available upon request

and is measured in three dummy variables: do not watch TV at all, watch TV but has no TV. Although the results are not shown[23], I find no effect of the program on employment and leisure time which suggest that switching to LPG might not have a significant effect on time allocation. This might be true in the context of developing countries based on anecdotal evidence that cooking task is assigned to mostly housewives who have low opportunity cost of lost time. Overall results seem to indicate that there is no significant indirect effects from these other outcomes, thus the effect of the program on infant mortality is could be mainly driven by the direct effect on the pollutants exposure.

2.4.4 Heterogeneous in the program effect

In this section, I test if the program has heterogeneous effects based on subsamples based on 5 categories: the duration, gender, rural/urban status, mother's education, and home ventilation. Table 2.8 shows the coefficient of the treatment effect from a regression with the base model including all the controls and the interaction with dummy program. The results are discussed below.

(1) Effect by duration. The effect of the program might be experienced soon after the reduction in the pollutant exposure and/or after long repeated periods of exposure. To see if such effect exists, I separately estimate the effect on household in early targeted districts (after 2008) and later targeted districts (after 2009). The result indicates that the effects are larger on households who got the program earlier. A possible explanation is that this effect includes both immediate effect on births and accumulated effect on the following births.

(2) Effects by gender. The results indicates a larger and significant effect on female infants. There are at least two possible explanation. First, in developing countries, gender discrimination often exist. If parents more likely to protect boys from pollution, more likely to provide medical treatments, then the program effect should be higher for girls. Parents maybe more concerned for boys' health compared to girls and thus unlikely to carry their infant while cooking. Thus

[23]Results are available upon request

improvement in the air quality does not affect boys because they are not as exposed as girls to the indoor air pollution. Second, there are large literature regarding boys being biologically weaker and more susceptible to environmental risks. Female fetuses have a higher threshold at which pollution leads to mortality than boys do. If the air quality improvement is somewhat still higher than pollution threshold for infant male, then the results should not reflect any changes in infant male mortality.

(3) Rural/urban status. The results show stronger effects on rural area. It supports the hypothesis that low-socioeconomic households are benefited more by the pollution reduction given that there are more poorer households in rural area. A possible explanation is that the effect on infant mortality rate in urban areas might be offset by the outdoor air pollution which are growing due to economic expansion after the financial crisis 2007-2008. There are also more health care access in urban areas.

(4) Mother's education. The results suggest that infants from low educated mothers are benefited more from the program. It could be that mothers with low education already have a low health endowment which initially made them more prone to the air pollution. Alternatively, mothers with higher education tend to know how to protect their children from the pollution by not carrying them while cooking or by having more access to health facilities to treat their children.

(5) Home's ventilation. Dasgupta et al. (2004) find that location of kitchen has large and statistically significant effects on 24-hour average indoor pollutants concentration, while Pitt et al. (2006) which find that an increase in the permeability of roofs or walls has no significant effect on health. I test this by using a question in the 2007 and 2012 survey: "where food is cooked? in the house/in separate building/outdoors". I construct a dummy of whether food is cooked in the house. Note that this question is not available in the 2002 survey, and there are many more households that cook inside compared to outside. Consistent with Dasgupta et al. (2004), the results show that the reduction in the infant mortality is significant for households who cook inside the house. The program has no effect on infant mortality on household who cook outside, as the health risk of burning dirty fuel is less when there are a lot of air circulation. Moreover,

households who cook outside are usually households who use wood fuel and not being targeted in the program.

Table 2.8: Heterogeneous effects on infant mortality within subgroups

Subsamples		Treatment		Constant		Observations	R-squared
(1) Program time	Start in 2009	-0.012**	(0.005)	-0.006	(0.047)	25,654	0.059
	Start after 2009	-0.010*	(0.005)	0.196	(0.220)	29,935	0.053
(2) Gender	Male	-0.005	(0.006)	0.002	(0.064)	20,346	0.065
	Female	-0.019***	(0.006)	0.428	(0.332)	18,542	0.059
(3) Location	Rural	-0.015***	(0.006)	0.196	(0.217)	25,886	0.058
	Urban	-0.008	(0.006)	-0.376	(0.276)	13,002	0.068
(4) Mother's education	Higher than secondary	-0.003	(0.005)	-0.060	(0.052)	21,558	0.050
	Low education	-0.027***	(0.008)	0.220	(0.217)	17,330	0.071
(5) Ventilation	Cook inside	-0.011**	(0.005)	-0.074**	(0.035)	23,018	0.063
	Cook outside	-0.008	(0.014)	0.015	(0.122)	4,323	0.124

Notes: Samples are split based on five categories in the first column. All regressions include all control variables and the interaction with post program dummy. The outcome variable is infant mortality. Standard errors (in parentheses) are clustered by district. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

2.4.5 Further Robustness Checks

The findings above demonstrate the consistency of the magnitude and the significance of the program effect across different set of controls. In Table 2.9, I extensively explore the result sensitivity to the sample selection, different unobserved trend at regional and provincial level, matching estimator, clustering, and placebo treatment.

Inclusion of excluded districts. I check robustness to the inclusion of the excluded districts, using three different strategies: household fixed effects strategy is used in column (1), Coarsened Exact Matching (CEM) (Blackwell et al., 2009) is used in column (2) and propensity score matching (Rosenbaum and Rubin, 1983) is used in column (3). Column (1) uses only survey wave 2012 which allows me to track all the birth records within the same household[24]. The coefficient shows within household effect of the program on infant mortality conditional on month of birth and mother's age at birth. It shows that the reduction in

[24]Note that the maternal and birth characteristics are only recorded for births occurred within 5 years preceding the survey, thus in this exercise I do not control for any maternal and birth characteristics. I limit the last ten births (2002-2012) to maintain some degree of comparability.

the infant mortality within household is mainly driven by the difference on the program status not by the unobserved differences at household level. In column (2), I balance the treated and untreated districts by wealth index, first birth, young mother, electrification, recall period, birth order, age at birth, singleton or multiple births, non-smoking behavior among household in the same province. The sample includes all districts (including previously excluded districts) and all three years of survey. Using the calculated CEM weights and year of birth fixed effects do not change the results. Propensity score matching methods in column (3) shows similar result. These results indicate that the program effect on the infant mortality are not driven by the excluded districts.

Unobserved policy changes. There might concurrent local policy changes on regional and provincial level. One region is lead by a governor and rule up to 22 districts while one province consists up to 4 regions and each is a separate island. Column (4) uses regional dummies interacted with year of birth as additional control variables (there are 22 regions). Column (5) has province dummies interacted with year of birth as additional control variables (there are seven provinces). The results confirm that the effect is not driven by yearly trend of the local policy changes at regional or provincial level.

Standard errors clustering. Column (6) replaces district clustering error term to region clustering error term to allow serial correlation within region (there are 33 regions). The result is very similar either clustering at districts or at regions.

First year after the program. As discussed in Section 2.3, I exclude the first year of the program implementation since there is limited information on which month the targeted districts got the program. The result in column (7) shows that the effect is insensitive to this first year exclusion. Similar with the results in column (1) - (3), this shows that the program effect on infant mortality is robust in every slice of the sample.

Aggregated to district level. I aggregated the infant mortality rate into district level data by year of birth. Column (8) shows the effect of the program on aggregated infant mortality rate on district level. Although the sample size is reduced significantly, the treatment effect is still significant with a slightly lower than with child level analysis.

Placebo test. I use a placebo treatment on the pre program sample data. The result in column (8) shows that infant mortality rate prior to the program is similar between targeted and untargeted regions.

Table 2.9: Additional robustness checks on infant mortality

	2012 panel	Coarsen exact matching	Propensity score matching	Regional trend	Provincial trend	Clustering	1st year excluded	Panel district	Pre program
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment	-0.011*	-0.011**	-0.012***	-0.011*	-0.010**	-0.011***	-0.011**	-0.009*	
	(0.006)	(0.005)	(0.002)	(0.006)	-0.004	(0.004)	(0.005)	(0.005)	
Placebo treatment									-0.001
									(0.005)
Household FE	Yes	No	No	No	No	No	No	No	No
District FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Region-year FE	No	No	No	Yes	No	No	No	No	No
Province-year FE	No	No	No	No	Yes	No	No	No	No
ControlsXPost	No	No	No	Yes	Yes	Yes	Yes	No	Yes
Cluster	264	264	264	264	264	33	264	264	264
Observations	39,947	32,398	49,201	38,888	38,888	38,888	38,550	4,255	25,551
Sample	2012 only	CEM matched	Common support	All	All	All	Excluded first year	District aggregated	2002, 2007

Notes: Column (1) uses survey wave 2012 and household fixed effects. Column (2) uses Coarsened Exact Matching and the regression is based on the common support weighted by CEM weights. Column (3) uses propensity score matching and the regression is based on the common support. Column (4) adds the interaction between region dummies and year of birth. Column (5) adds the interaction between province dummies and year of birth. Column (6) uses clustering standard errors at regional level. Column (7) exclude the first year of treatment. Column (8) uses aggregated infant mortality by district, controlling for dummy survey year. Column (9) uses placebo treatment as if the program was started 5 years before the actual program. Standard errors (in parentheses) are clustered by district. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

2.5 Policy Implication

This study suggests that access to cleaner fuel for cooking can lead to an improvement in health. In terms of the monetary benefit, replacing kerosene with LPG in over three years led to approximately USD 2.9 billion net saving from the removal of kerosene subsidy (Budya and Arofat, 2011). Even ignoring the health benefit, the program still gives a positive net benefit, although there is little known on the negative effect of the program that could offset its positive benefit. By 2011, the program is estimated to reduce 717 infant deaths annually based on 19.95 birth rate per 1,000 population on 91 million total population in the targeted regions. Using a lower bound value of statistical life of USD 4 million (Viscusi and Aldy, 2003), the benefits from these avoided deaths yield an estimated USD 2,8 billion in annual savings. If the program is expanded to the remaining untargeted regions after 2011, the program could lower infant death by almost 299 lives annually (calculated based on 37 million total population in the untargeted regions). It yields to an estimate of USD 2 billion annual savings. The health benefit of the program covered in this study is limited to infant mortality, but there is still possibility of other health benefits such as respiratory illnesses and adult morbidity (Smith et al., 2013). Moreover, potential benefit outside of health might also worth looking at, such as labor force and the environmental impact. Budya and Arofat (2011) has section that discuss about new investment in LPG leading to 28 thousand new jobs and an approximate reduction in CO_2 emissions by 8.4 million tonnes per year due to this program.

About half million of the premature deaths attributed to air pollution stem from pollution contributed by indoor air pollution, which made it one of the largest public health issue in developing countries(Smith et al., 2013). Even moving away from kerosene, a cleaner fuel compared to solid fuel, can lead to a tangible health benefit. Thus, moving away from solid fuel is expected to have even greater health benefits. This study should at least provide the lower bound estimates on the health benefit on converting to cleaner cooking fuel. In Indonesia, households who use solid fuel accounts for a major portion of the population (at least 50% of the country's total population). Even though LPG is not the cleanest fuel among others such as natural gas, electricity or renewable energy, it is the cleanest among other dirty fuels such as solid fuels. It is also the most affordable clean household energy in many developing countries.

There are many kinds of interventions in household energy. This program provide an example of how pricing and quantity strategy might work to encourage fuel switching. Without a government intervention, households often do not have the incentives to switch to cleaner fuel(Mobarak et al., 2012). This program is unique compared to many other LPG programs in other countries as the switching to LPG is rather enforced in nature. The subsidized kerosene was removed once the program rolled out in the targeted districts. Another example is India who has succeeded in implementing their 'Give it Up' program, a unique initiatives that encourages altruistic motives from middle to high income households to voluntarily give up their LPG subsidy to poorer households(Singh et al., 2017). The optimal policy for household energy conversion which can better target the poor is still an open question but it is an important aspect in reducing energy poverty. Adding to Kojima (2011) who gives an optimistic review on the role of LPG in reducing energy poverty, this study also provides some health evidence of switching from kerosene to LPG.

2.6 Conclusion

In mostly developing countries, over 90 million people use kerosene for cooking. It has been highly subsidized with USD 18 billion total subsidy per year (Mills, 2017). Given the high level of subsidy and potential adverse health risks of kerosene, policy makers start to consider supporting other cleaner fuel such as LPG. The complete analysis of a policy requires the full information on cost-benefit, including health benefits. Reliable estimates on the effect of household fuel conversion to the health outcomes is one of the primary elements missing in the conventional cost-benefit analysis. There are lessons to learn from Indonesia's mega project on household fuel conversion. This paper documents its benefit on early life health outcomes, the possible mechanism and its effects across groups.

This study provides a lower bounds on the benefit of cleaner energy access to infant mortality rate because it is based on the live births population. For example, mothers who suffer from fetal losses might decide to not become pregnant. Hence, the children in the sample are born from mothers who are generally healthier than those who decided to not become pregnant. This study also does not intend to show a dose-response relationship between indoor air pollution and health, but focuses on the average treatment effect from having access to a cleaner cooking fuel. Nonetheless, it provides the first estimation on the health benefit from switching from kerosene to LPG which is shown to have significantly greater health benefit to the most vulnerable group, the poor households with low education. Overall, such program intervention on subsidizing cleaner cooking fuel is one way to achieve the United Nations' Millennium Development Goals.

Chapter 3

Variable Pricing and the Cost of Renewable Energy

[1]

3.1 Introduction

How much will it cost to eliminate use of fossil fuels? There is reason for optimism. Technological progress has lowered the cost of wind and solar power to make them increasingly competitive with coal and natural gas on a levelized basis. Battery storage costs are also falling, which should grow electric vehicle use and could help electric grids absorb intermittent renewable energy when it happens to be plentiful. Increasing integration of markets across regions and countries could further facilitate adoption of wind and solar, as they allow more flexible trading of power from times and locations with relatively high supply to those with relatively little. Nevertheless, recent research indicates that intermittency combined with the high cost of storage greatly increases the cost of renewable energy from a system perspective Gowrisankaran et al. (2016).

A key challenge is that modern infrastructure has been built around electrici-

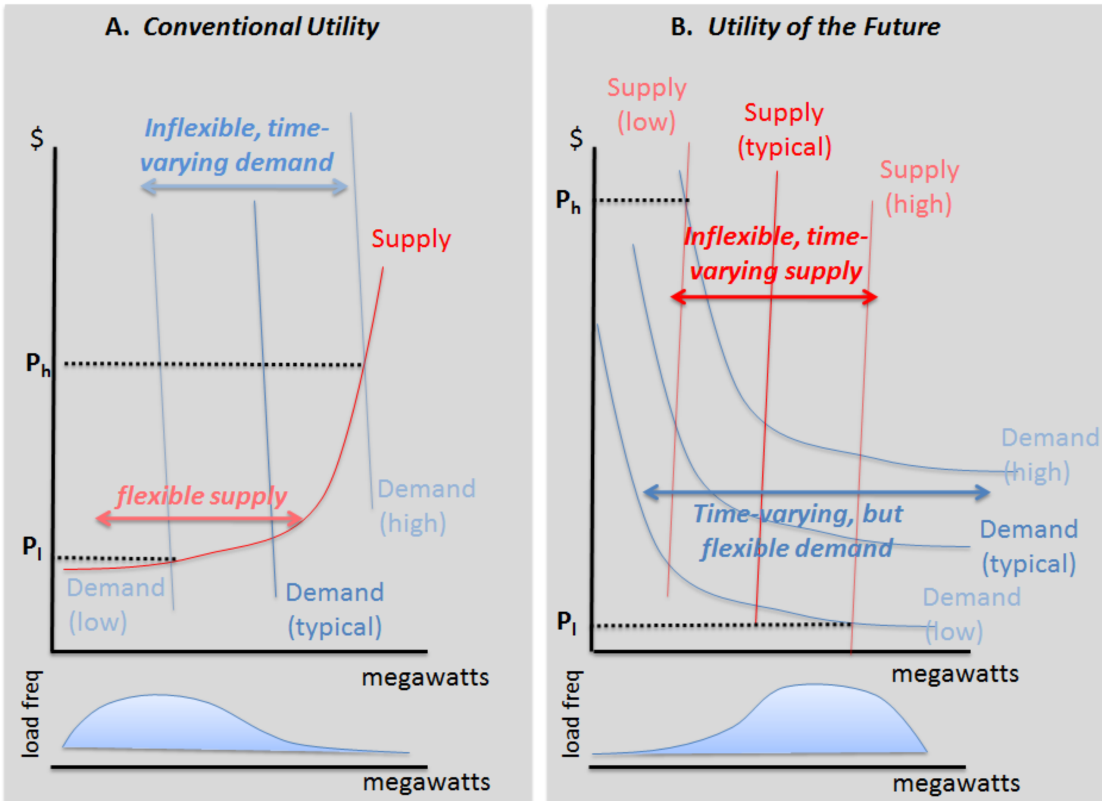
[1]joint work with Michael J. Roberts and Matthias Fripp

ty systems with centralized and easily controllable generation. Electric grids operate through balancing authorities that adjust electricity generation on timescales ranging from seconds to years, to perfectly balance presumably inelastic, time-varying demand (Figure 3.1, panel A). Although marginal generation costs vary over time in a conventional system, regulated retail prices tend to be flat, giving rise to well-known inefficiencies. But since incremental costs only spike during rare peak loads, the inefficiencies from flat rates are thought to be small, with most concern centered on market power as demand approaches capacity constraints Borenstein and Holland (2005); Borenstein (2005); Blonz (2016). Utilities and generating companies have little incentive to change the current system, possibly because too few are aware of the possibilities associated with variable prices, or because it may not benefit them under cost-of-service regulatory structures that currently predominate at the distribution level. Customers have also been unenthusiastic about dynamic marginal-cost pricing, possibly because they lack confidence that they would individually benefit from it. The smoothing of costs when setting retail rates makes demand highly inflexible (inelastic) with respect to generation cost on a day-to-day, hour-to-hour basis, and current system planning and operation reflect this inflexibility.

Balancing almost entirely on the supply side and foregoing potential demand response creates some deadweight loss in existing power systems, but the loss will be much greater in power systems with a large share of intermittent renewables. Solar and wind power are the most cost-effective renewables, but the supply varies with sunlight and windspeed. When intermittent renewables make up a small to moderate share of total generation, the existing infrastructure can accommodate their variability in much the same way it has always managed variable demand. Variations in renewable energy are counterbalanced with directed variation in generation from fossil fuel plants. But as larger shares of renewable energy are accommodated using this conventional model, system-level costs may rise significantly above the levelized costs from any particular source. Controllable generation must be built or retained to compensate for periods of low renewable power production, and these plants may burn either polluting fossil fuels or high-cost biofuels. Providing spinning reserves from thermal power plants — ramping them up and down to compensate for short-term variations in demand or renewable production — requires running these plants at inefficient fractional load levels. Moreover, as more intermittent renewable power is added to the grid, eventually supply begins to exceed demand and storage capacity at certain times, and renewable energy must be curtailed (i.e., discarded). This creates diminishing returns for renewable power and raises average costs. In Hawai'i, Texas, Ireland and perhaps other places, a considerable amount of electricity is already curtailed, even while utility customers may simultaneously pay 30 cents per kWh or more for electricity. With retail prices far above the incremental cost of generation (zero or negative during curtailment), there appears to be inefficiency in the current system, even with renewable energy penetration far below the eventual goals in state renewable portfolio standards. Resolving this inefficiency would help to slow climate change.

To economists, the obvious solution to intermittency is real-time retail pricing that reflects the incremental cost and marginal willingness to pay for electricity. If electricity were priced at its incremental value and cost there would be new, powerful incentives to efficiently store energy on a distributed basis or otherwise shift consumption from times and places of relatively scarce renewable supply to times and places of plenty. Chemical storage of electricity in batteries or hydrogen remains expensive. However, critically, and potentially transformationally, electricity consumers already have access to many low-cost systems that store energy in different forms. By carefully timing water heating, electric vehicle charging and water pumping, using ice storage for cooling systems, making micro-adjustments for some kinds of refrigeration, or perhaps other means, electricity use can be shifted from seconds to many hours at low cost. Such mechanisms would need to be automated by smart devices acting on customers' behalf. These existing technologies can make electricity demand highly substitutable over time, at least over horizons up to a day or so. In addition to shifting the timing of electricity consumption within the day, customers facing dynamic prices can also adjust the total amount of power they consume each day, reducing total consumption during extended periods when power is scarce, or increasing it when power is abundant. We conceptualize this substitutability and overall elasticity with a more elastic

Figure 3.1: Conventional Utility and Utility of the Future



Notes: Intermittent renewables change the nature of the utility. The horizontal axis is power generated or consumed at a point in time, and the vertical axis is incremental willingness to pay (Demand) or incremental cost of generation (Supply). A stylized frequency distribution of load is shown at the bottom. Panel A shows a conventional utility with flexible supply that can ramp generation up and down with varying demand without greatly changing the incremental cost of power, except for rare peaking loads, so prices are typically low (P_l). Welfare gains have been gleaned from curbing peak loads with critical-peak pricing and demand charges for commercial users, which tie each firm's incremental price to its historical peak. Panel B shows a hypothetical utility of the future, with generation coming mainly from inflexible, time-varying intermittent renewables and real-time pricing. With highly volatile time-varying prices, storage and shiftable loads cause demand to become more flexible, especially in the lower price range, but prices can spike very high during unusual periods when supply is low and demand high.

demand in panel B of figure 3.1. While demand-side flexibilities would make intermittent renewable energy more cost effective from a system perspective, they will only be brought to market and adopted if pricing mechanisms incentivize them.

In this paper we develop a novel model of power supply and demand to examine the extent to which variable pricing could plausibly increase the social benefits of renewable energy. The model is novel in the way it integrates investment in generation and storage capacity with real-time operation of the system, including an account of reserves, a demand system with different interhour e-lasticities for different end uses, as well as substitution between electric power and other goods and services. Both supply and demand sides of the model can also provide reserves. The model, an extension of Switch Fripp (2012); Johnston et al. (2017), is open source and adaptable to other settings. Earlier versions of the model (lacking reserves and demand-side integration) have been implemented for California, the Western United States, and other areas Fripp (2012); Nelson et al. (2012); Mileva et al. (2013); Wei et al. (2013); Ponce de Leon Barido et al. (2015); Sanchez et al. (2015); He et al. (2016).

Our study considers the island of Oahu, the most populous island (about 1 million) and county of Hawai'i, which comprises roughly two thirds of the state's population and consumes over three quarters of the state's power. The island supports a large urban city (Honolulu), plus a substantial tourist industry and several large military bases. Hawai'i is a particularly interesting focus for several reasons. First, its scale is large enough to be emblematic of larger, more complex systems, but small enough to be holistically modeled. Second, given Oahu's isolation and lack of connectivity to other Hawaiian islands, intermittency is an especially acute problem, since connectivity and trade with other regions is not economically feasible. Third, Hawai'i has the nation's, and perhaps the world's, most ambitious renewable portfolio standard – 100 percent renewable by 2045 – which makes our analysis especially relevant to actual policy implementation. Fourth, Hawai'i depends on oil for its power production, making wind and solar power cheaper than fossil fuels today, so it is first to face an economic crossover that other regions will face in the future, as wind and solar move toward undercutting natural gas and coal.

We use the model to: (1) estimate the cost, benefits and optimal generation mix of a 100 percent renewable energy system that accords with Hawai'i's renewable portfolio standard (RPS) as compared to a conventional fossil-fuel power system (Fossil) and a least-cost system with no constraints on the generation mix (Unconstrained); (2) evaluate the welfare improvement of having dynamic marginal-cost pricing as compared to flat price for each kind of system (RPS, Fossil, and Unconstrained); (3) evaluate how much those with high interhour substitutability of demand gain from dynamic pricing as compared to those with very little interhour substitutability.

Cost assumptions for a wide range of power generation and storage alternatives, from which an optimal portfolio is selected by the model, are based on those in the most recent (December, 2016) Power Supply Improvement Plan (PSIP) of the local utility, Hawaiian Electric Company (HECO).[2] We consider scenarios for which costs equal current-day assumptions, as well as scenarios that use the lower costs projected for renewable and battery technologies in 2045 in the PSIP. The analysis we perform here is a single-stage analysis in the sense that each scenario assumes the optimized system is built at one point in time, although pre-existing assets can be retained. We do this to make clear comparisons of highly-renewable and fossil systems in flat and dynamic pricing contexts, and to show how much renewable power would be selected in optimized systems with fixed versus dynamic marginal-cost pricing. In practice, an optimal plan would make investments gradually over time; Switch does have the capacity to formulate such a plan, even though we do not consider it in this paper. Such a model would be considerably slower to solve.

Consistent with earlier studies, we find that dynamic pricing of power provides little social benefit in fossil-fuel systems, only 2.6 to 4.6 % of baseline annual expenditure depending on cost and interhour substitutability. But dynamic pricing leads to a much greater social benefit of 8.5 to 23.4% in a 100% renewable system with otherwise similar assumptions. The other key finding is that high penetration renewable systems, including 100% renewable, are remarkably affordable. Indeed, the welfare maximizing (unconstrained) generation portfolio under the utility's projected 2045 costs and pessimistic interhour demand flexibility uses 79% renewable energy and improves welfare by 34.6% of baseline expenditure. With dynamic pricing, even a 100% renewable system is welfare improving over a fossil system, excluding gains from reduced pollution externalities. These results all derive from an assumed outer demand elasticity of just 0.1, and cost assump-

[2]See `https://www.hawaiianelectric.com/about-us/our-vision`.

tions for renewable energy and batteries that some may regard as pessimistic. In other scenarios the benefits of real time pricing paired with renewable energy can be far greater.

The rest of the paper is organized as follows: Section 3.2 characterizes the demand system and how we calibrate it; Section 3.3 reviews the Switch model that optimizes investment and operations, as well as a Dantzig-Wolf algorithm used to equilibrate supply and demand and thereby optimize the joint system; Section 3.4 summarizes capital and input cost assumptions and the wide range of scenarios we consider; Section 3.5 summarizes the results; and Section 3.6 concludes.

3.2 Demand

The main novelty of this paper is the integration of a fully-specified interhour demand system with Switch, a state-of-the-art planning model that jointly optimizes investment and chronological, hourly operation of a power system. We therefore begin by describing the structure of the demand system and how we calibrate it.

3.2.1 A Nested-CES Demand System

The demand system is comprised as the sum of three nested, constant elasticity of substitution (CES) utility functions that represent different types of demand. The outer layer of each utility function assumes just two goods, electricity and all other goods, with a constant elasticity of substitution θ, which represents a demand elasticity. The nested layer considers electricity demand in each hour within each 24-hour day, with an interhourly elasticity of substitution σ. Aggregate demand in any given day is comprised as the weighted sum of three representative pseudo-customers with different σ values. Each pseudo-customer is assumed to maximize utility $U(x_1, x_2, \ldots, x_h, \ldots, x_{24}, Y|\sigma, \theta, \alpha, \beta_1, \beta_2, \ldots, x_h, \ldots, \beta_{24})$ subject to their budget constraint, $\sum_{h=1}^{24} p_h x_h + Y = M$, where x_h is electricity consumed in hour h, Y represents expenditure on all other goods with a constant price equal to 1 (i.e., money), α and β_h are share parameters that weight all other goods relative to electricity, and electricity in each hour relative to other other hours, and M is total income. M is calibrated by dividing total baseline electricity expenditure of a particular pseudo-customer in a day by the share of aggregate income spent on electricity. The α and β_h parameters are calibrated from the statewide share of income spent on electricity expenditure, and by baseline load shares allocated to each pseudo-customer.

Following Rutherford (2008), suppose there exists a unit expenditure function or an ideal price index (the minimum expenditure required to achieve baseline utility) in the "calibrated share form," a measure relative to baseline values. The expenditure function is:

$$e(p_h, p_{(-h)}, \bar{p_h}, \bar{p_{(-h)}}, \bar{U}) = \bar{U}\left(\alpha\left(\frac{p_Y}{\bar{p_Y}}\right)^{1-\theta} + (1-\alpha)\left(\sum_{h=1}^{n}\beta_h\left(\frac{p_h}{\bar{p_h}}\right)^{1-\sigma}\right)^{\frac{1-\theta}{1-\sigma}}\right)^{\frac{1}{1-\theta}} \tag{3.1}$$

where $\bar{U}$, $\bar{p_Y}$, $\bar{p_h}$ indicate baseline values for respective parameters, α is the calibrated share given the baseline value of $\bar{Y} = M - \sum_h \bar{x_h}\bar{p_h}$, $\alpha = \bar{Y}/M$, and β_h are calibrated shares of each day's electricity consumed by the pseudo-customer in each hour at the associated baseline prices $\bar{p}_h$.

Consumer welfare is measured by the indirect money metric utility function. That is, we can write indirect utility in terms of the income required at baseline prices to achieve the utility level achievable at prices p and income M, as:

$$V(p_h, \bar{p}_{-h}, M) = \frac{M}{e(p_h, p_{(-h)}, \bar{p_h}, \bar{p}_{-h}, \bar{U})} \tag{3.2}$$

From Roy's Identity, Marshallian demand is given by:

$$x_h(e(p_h, p_{-h}, \bar{p_h}, \bar{p}_{-h}), M) \quad = \quad -\frac{\partial V/\partial p_h}{\partial V/\partial M} = \frac{M}{e}\frac{\partial e}{\partial p_h}$$

The closed form solution of demand functions then can be written as a function of calibrated share parameters derived from a baseline load profile and the share of income spent on electricity at baseline prices.

$$\frac{x_h(p|\bar{p},\sigma,\beta,M)}{\bar{p}} =$$

$$M\left(\alpha+(1-\alpha)\left(\sum_{j=1}^{24}\beta_j\left(\frac{p_j}{\bar{p_j}}\right)^{1-\sigma}\right)^{\frac{1-\theta}{1-\sigma}}\right)^{-1}\times(1-\alpha)\left(\sum_{j=1}^{24}\beta_j\left(\frac{p_j}{\bar{p_j}}\right)^{1-\sigma}\right)^{\frac{\sigma-\theta}{1-\sigma}}\times\beta_h\left(\frac{\bar{p_h}}{p_h}\right)^{\sigma} \tag{3.3}$$

In the computational model, we partition a baseline load profile, drawn from actual historical hourly demand, into three pseudo-customers, each with a different interhour substitutability parameter, $\sigma \in \{\sigma_l = 0.1, \sigma_m = 1, \sigma_f = 10\}$ and a different baseline demand profile, derived from historic loads. Pseudo customers thus differ with regard to their budget and with regard to their calibrated share parameters (β_h), because their load profiles differ. The calibrated share parameters also differ by day and season, to account for weather.

To formalize this demand system, denote the calibrated load shares on day d and pseudo-customer i by β^{id} and income by $M^{id} = \frac{E^{id}}{s}$, where E^{id} is the baseline expenditure of pseudo-customer i on day d, and s is the share of baseline state income spent on electricity. Thus, define the demand for a pseudo-customer i on day d in hour h as $x_h(p|\bar{p},\sigma_i,\beta^{id},M^{id})$, using the definition in equation 3.3. Aggregate demand on day d and hour h is given by the sum of the demands from the three pseudo-customers:

$$x_h^d(p|\bar{p}) = x_h(p|\bar{p},\sigma_l,\beta^{ld},M^{ld}) + x_h(p|\bar{p},\sigma_m,\beta^{md},M^{md}) + x_h(p|\bar{p},\sigma_f,\beta^{fd},M^{fd}) \tag{3.4}$$

This demand system provides an intuitive and relatively simple way to embody a range of heterogenous demand responses and inter-temporal substitutability of loads that vary over seasons and weather-related circumstances. The degree of interhour substitutability may under- or over-estimate actual technical possibilities. For example, it assumes the same degree of substitutability between any two hours within the same day. At least for some kinds of demand, substitutability may be greater for hours nearer in time. At the same time, the demand system assumes zero substitutability between days, when in reality substitution between late in one day and early in the next may be fairly elastic. While this later assumption may under-estimate the overall degree of flexibility, the structure makes it easy to scale up a sample of representative days throughout the year to parsimoniously represent a portfolio of days with weather and demand that are chronologically matched with supply.

3.2.2 Shares of Flexible Demand

This section describes how we estimate baseline loads for each kind of pseudo-customer. We used hourly aggregate demand data for Oahu from the Federal Energy Regulatory Commission to calibrate hourly load shares that are coincident with solar and wind data used in modeling the supply side. This allows the model to account for the covariances between renewable supply and demand. However, because some kinds of demand are likely to be more time shiftable than others, we develop alternative interhour flexibility scenarios based on estimated load shares that are known to be shiftable using current technologies: air conditioning, water pumping and water heating.

Air conditioning demand is shiftable using ice storage, wherein ice is generated when electricity prices are low, and used for cooling instead of running the compressor when electricity prices are high. These systems can be retrofitted onto existing air-conditioning systems. A number of companies already market this technology to reduce *demand charges*[3], to respond to real-time variation in prices, or provide contingency or regulating reserves to the balancing authority.[4]

[3]Demand charges, which are common for commercial electricity customers, link monthly bills to the highest kW draw, typically averaged over a 15-minute period, from each commercial customer during the month or year. However, because peak demand by an individual customer is unlikely to coincide with the system peak, demand charges may do little to improve efficiency relative to real-time pricing Borenstein et al. (2002).

[4]*Regulating reserves* balance the electricity system in real time as demand fluctuates from moment

Such systems may only require different, smarter controllers and network connectivity. A considerable amount of flexible power is also used to pump water from aquifers to storage reservoirs and tanks on hillsides; water is then gravity fed to homes and businesses. Currently, most water pumping is done at night, because the water municipality receives a slight discount under current time-of-use pricing. There should be a considerable amount of flexibility in when pumping could occur, a flexibility that is mainly constrained by the capacity of water storage. A number of companies have also developed smart water heaters, which can heat proactively in relation to power availability (or prices) and typical use patterns instead of reactively to hot water use. All of these systems embody an implicit form of storage that may be much less expensive than batteries, compressed air, pumped-water hydroelectricity or other means. These systems can also provide a source of reserves to help maintain system stability in the face of unexpected load fluctuations.

By considering loads from only these three principle sources, we believe our estimates of demand-response potential should be conservative, because other kinds of electricity demand for which we could not obtain estimates, or for which current technologies do not exist, may nevertheless prove shiftable if appropriate incentives and technologies were to be made available. For example, refrigerator/freezers and swimming pool pumps likely have large, time-shiftable loads, but we do not explicitly consider them in this study because we were unable to obtain data on their real-time use.

Another consideration is that over 70 percent of total demand on Oahu derives from commercial customers, many of whom have electricity metered at 15 minute intervals or less to accommodate demand charges specified in commercial tariffs. The state is also developing plans to install smart meters for other customers. Even without smart meters, we expect that integrators could implement a wide range of demand-response services, including reserve provision, by using other forms of network connectivity to control power consumption of certain

to moment while *contingency reserves* keep the system stable in response to larger disruptions, such as a power plant unexpectedly falling off line.

designated devices. Alternatively, devices could be programmed to forecast and respond to price signals automatically.

Estimates of shiftable load in each hour of each month are drawn from Navigant Consulting (2015), a private consulting report commissioned by Hawaiian Electric, a copy of which was submitted to the Public Utility Commission. Although much of the report is redacted, obscuring the methods used to estimate load shares from alternative uses, it is the only available load share data, specific to Oahu, that we have been able to obtain. The starting point for our estimates is a graph in the report depicting September 2025 projected end-use loads by hour of the day. We measured the bars in the graphs by hand to estimate load shares in each hour for this month, and summed those for air conditioning, water heating and water pumping to obtain an estimate for the mid-September share of potentially shiftable load. Because loads vary over time, and tend to be higher when it is warmer, presumably due to greater use of air conditioning, we adjusted load shares for other months to account for this seasonality. We made this adjustment using hourly load estimates provided in the Navigant report for February, May, August and November of 2014, but were not partitioned by end use. These hourly loads were regressed against a polynomial of hour-of-day and average temperature in each month.

$$\text{Load} = \beta_0 + \beta_1 h + \beta_2 h^2 + \beta_3 h^3 + \beta_4 PV + \beta_5 \text{T}.$$

where h is hour per day, PV is distributed generation from photovoltaic solar (which may be associated with temperature), and T is temperature. We attribute temperature-sensitive load to air conditioning, and then using load shares given for September 2025 as a baseline, we infer the air conditioning share for the other months, linearly interpolating between February, May, August and Noveember. Load shares attributable to water pumping and water heating is assumed to be same across all months of the year.

We consider three different scenarios (optimistic, moderate, pessimistic), each of which assigns different shares of the potentially-flexible and other load to pseudo-customers with different interhour substitutability. The assumptions for each scenario are reported in table 3.1. In figures 3.2 and 3.3 we plot the implied shares of highly flexible, moderately flexible, and inflexible demand in total and by hour and month for each of the three scenarios.

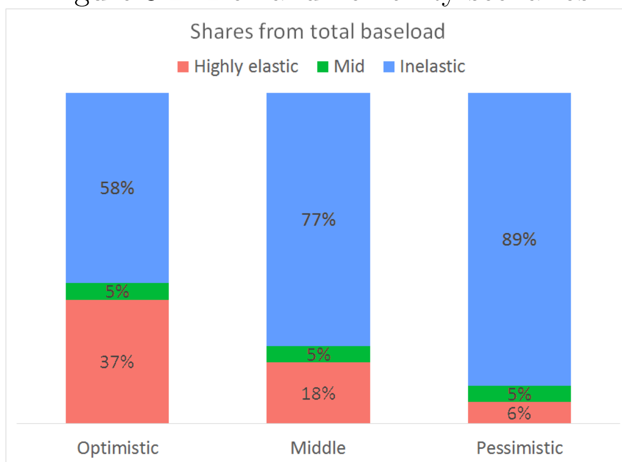
In the end, we cannot know in advance how much demand is truly flexible or the appropriate elasticities to use, nor anticipate how much potentially flexible customers will choose to engage with a well-designed variable-pricing program. We anticipate that commercial customers would comprise the bulk of participating flexible demand. Because commercial customers comprise over 70% of Oahu's load and commercial loads have a large share of potentially-shiftable load, the optimistic scenarios assume that a large majority, but not all, of commercial customers with shiftable load would actively participate in a demand response program. That optimistic scenario might be justified by the historically high participation of commercial customers in real-time marginal-cost pricing programs like the one in Georgia. We anticipate that participation could be even greater in future Hawai'i, since price variation will presumably be far greater and advanced computing technologies could make participation convenient and relatively low cost.

Table 3.1: Share of shiftable load

	σ	Optimistic	Moderate	Pessimistic
Share of potentially flexible load (water pumping, water heading and air conditioning)				
Highly Flexible	10	67%	33%	15%
Somewhat Flexible	1	5%	5%	5%
Highly Inflexible	0.1	28%	62%	80%
Other load				
Highly Flexible	10	15%	8%	0%
Somewhat Flexible	1	5%	5%	5%
Highly Inflexible	0.1	80%	88%	95%

Notes: Shares of flexible and inflexible shares in each scenario.

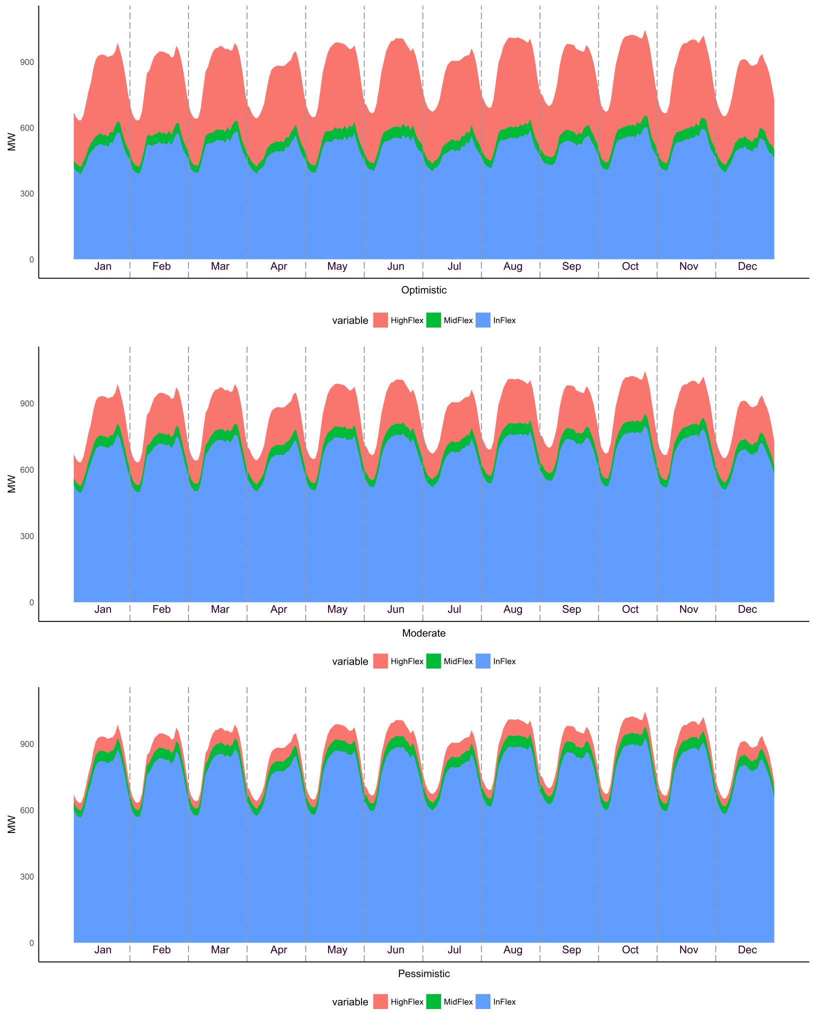
Figure 3.2: Demand flexibility scenarios



3.2.3 Demand-Side Reserves

Up reserves normally refer to residual capacity by dispatchable generators that can ramp up in the event that a power plant drops offline, wind or solar energy generation unexpectedly falls, or demand suddenly spikes. Reserves can also be provided by the demand side, and this is typically what power engineers call *demand response*, while economists normally connect the term to the more general idea of price-sensitive demand. Historically, demand-side up reserves have involved contracts between the balancing authority (e.g., utility or ISO) and large-scale users of electricity that give the balancing authority the ability and right, in exchange for a rate reduction, to remotely reduce or terminate power supply to participating customers during certain critical events (note that "up" reserves are specified from a generation perspective, so they correspond to *reducing* load). In Hawai'i, residential customers have also participated in a program that gives residential customers a \$3 monthly discount in exchange for allowing the utility to suspend power supply to water heaters during critical events. Similarly, *down reserves* correspond to the option of quickly ramping down a power plant or increasing energy use in the event of a net supply surge, which might result from a sudden falloff of demand or supply surge from intermittent renewables.

Figure 3.3: Demand flexibility scenarios by hour and month



The graphs show three scenarios for interhour demand flexibility, optimistic, moderate, pessimistic, respectively. Note that all demand types are assumed to have the same overall demand elasticity for electricity (0.1 in the the baseline case). Flexible, midflex and inflexible loads are assumed to have within-day interhour elasticities of substitution equal to 10, 1 and 0.1 respectively.

The model presented here includes demand-side participation in reserve markets for both up and down reserves, with only highly-flexible demand types assumed to participate. Reserves can also be supplied by the supply side, either from batteries or dispatchable generators. On the demand side, we incorporate reserve provision into flexible-type demand by applying a net cost that includes sale of up and down reserves and purchase of energy, all at real-time prices. We define these as follows:

$$x_h^u = x_h^* \tag{3.5}$$

$$x_h^d = \max(x_h) - x_h^* \tag{3.6}$$

where x_h^* is energy use in hour h, x_h^u is demand-side up-reserves provision (option to decrease demand) in hour h, x_h^d is demand-side down-reserves provision (option to increase demand) in hour h, $\max(x_h)$ is the maximum electricity demand when price equals an imposed minimum ($1 per MWh). The minimum price limits demand that could otherwise rise to infinite levels given the constant-elasticity structure of the demand system. The flexible pseudo-customer chooses x_h^* (and implicitly x_h^u and x_h^d), resulting in a net cost given as follows:

$$\text{Net Cost} = p_h^* x_h^* + p_h^u x_h^u + p_h^d x_h^d \tag{3.7}$$

$$= p_h^* x_h^* + p_h^u x_h^* + p_h^d \cdot (\max(x_h) - x_h^*) \tag{3.8}$$

$$= x_h^* \cdot (p_h^* + p_h^u - p_h^d) + p_h^d \max(x_h), \tag{3.9}$$

i.e., the incremental cost per unit of consumption is $p_h^* + p_h^u - p_h^d$.

3.2.4 Calibration of Hourly Demand Shares

We calibrate demand scenarios by estimating the share of aggregate load in each hour and each month used for three potentially shiftable loads: water heating, water pumping and air conditioning. Typically these uses of power can be shifted many hours at relatively low cost using existing technologies. We then suppose optimistic (67%), midline (33%) and pessimistic (15%) scenarios, each of which assumes a different share of these potentially-shiftable loads will actually have high interhour substitutability within a day (elasticity = 10). Across all scenarios we assume just 5% of baseline demand has moderate substitutability between hours (elasticity = 1). We assume that 80-95% of remaining load (not for water heating, water pumping or air conditioning) is highly inelastic between hours (elasticity = 0.1). The optimistic scenario could be achieved with widespread adoption of real-time pricing and automated demand-response systems by commercial users alone.

We use a baseline model that assumes an overall demand for energy (capturing substitution between electricity and all other goods) that is highly inelastic (elasticity = 0.1), which is consistent with a recent estimate with a strong study design and relatively similar climate and marginal price profile Ito (2014). While some studies find larger demand elasticities, they tend to be based on poorer study designs and we believe it is important to have a baseline model that is reasonably conservative. Within our model, this outer elasticity captures demand response over longer time horizons, which helps with seasonal imbalance and episodic weather, and adjusts overall scale modestly depending on average prices. However, because it seems possible that new technologies and energy demands might arise in a world with highly variable (and often free or nearly free) electricity, we also consider scenarios with larger demand overall elasticities (0.5, 0.9 and 2.0).

3.2.5 Electric Vehicles

An important consideration for modeling future power systems with high-penetration renewables is the potential growth of electric vehicles. Electric vehicles represent a new source of power demand and, given their large and growing battery sizes, a new source of power storage or interhour flexibility that might also provide reserves. Like demand-side flexibility, it is highly uncertain how quickly electric vehicles may grow as a share of the vehicle fleet. Given the unique nature of power demand from electric vehicles, plus the fact that they comprise a small share of historical loads used to calibrate the demand functions described above, we treat them separately. We also consider scenarios with a wide range of electric vehicle adoption, 0.5% (the current share), 50% and 100%. In variable pricing environments we assume that vehicle charging is optimally scheduled to least-cost times in each day, and thus makes high-penetration renewable systems easier to achieve, but do not allow for any interday substitution of charging (which will likely be feasible). In fixed-price environments we assume vehicle charging occurs as soon as vehicles arrive at home or work, based on trip inventories from the National Household Travel Survey Fripp (2017); Das and Fripp (2015); FHA (2009). This shifts up the evening peak more than other times, and makes high-penetration renewable systems more costly.

3.3 Switch 2.0

Switch[5] Fripp (2012); Johnston et al. (2017) is open-source power planning software that uses mixed-integer linear programming to minimize the net present value of the cost of electricity production subject to operation and policy constraints. The main decision variables are generation capacities at each candidate project site and the amount of power to produce or store at each project site during each hour of the planning period. Constraints require adequate power to satisfy demand plus reserves during all hours, and satisfaction of any exogenous policy constraints, such as a renewable portfolio standard (RPS).

Switch combines an operational model, similar in detail to production cost models such as GE MAPS or Plexos, and a long-term capacity expansion model, similar to Ventyx Strategist or PowerSimm Planner. Commercial capacity planning models typically consider the distribution of loads exogenously imposed on a system, neglecting price response by customers. Moreover, conventional planning or expansion models generally use unordered sets of time steps, and

[5]http://www.switch-model.org

thus do no have enough temporal detail to model the operation of power systems with a large share of time-varying renewables. Such power sources may need to be curtailed or be balanced by interhour load shifting or energy storage, which can only be modeled accurately with chronological time steps. In contrast to conventional capacity planning models, conventional production cost models can optimize chronological management, but assume fixed generation portfolios that must be selected by other means. Efficient integration of renewables can be greatly enhanced by simultaneously considering both capacity and chronological operation decisions, as does Switch Fripp (2012); Johnston et al. (2017); Nweke et al. (2012); Sullivan et al. (2014).

3.3.1 Mathematical Formulation of Switch

Here we provide a brief overview of the core equations used by Switch. A more complete documentation of the software can be found in Johnston et al. (2017).

Switch 2.0 has a modular architecture that reflects the modularity of actual power systems. Most power system operators follow rules that maintain an adequate supply of power, and most individual devices are not concerned with the operation of other devices. Similarly, core modules in Switch define spatially and temporally resolved balancing constraints for energy and reserves, and an overall social cost. Separate modules represent components such as generators, batteries or transmission links. These modules interact with the overall optimization model by adding terms to the shared energy and reserve balances and the overall cost expression. They can also define decision variables and constraints to govern operation of each technology. This approach makes it possible for users to add, remove or alter modules, representing different system components and formulations without unexpected interactions with other parts of the model. Consequently, Switch 2.0 can be readily customized to address the needs of a given study or region.

In the treatment below, we have omitted elements that define regional load zones and power transfers between these zones, since our model of Oahu has only a single zone. However, transmission constraints would be of critical importance for applications to larger geographical areas that are connected, such as the continental United States. We have similarly omitted definitions for multiple investment periods, since we use a single stage for this study.

3.3.1.1 Objective Function

The objective function minimizes the net present value of all investment and operation costs:

$$\min \sum_{c^{\mathrm{f}} \in \mathcal{C}^{\mathrm{fixed}}} c^{\mathrm{f}} + \sum_{t \in \mathcal{T}} w_t^{\mathrm{year}} \sum_{c^{\mathrm{v}} \in \mathcal{C}^{\mathrm{var}}} c_t^{\mathrm{v}} \tag{3.10}$$

Function (3.10) sums over sets of fixed costs $\mathcal{C}^{\mathrm{fixed}}$ and variable costs $\mathcal{C}^{\mathrm{var}}$. Each fixed cost component $c^{\mathrm{f}} \in \mathcal{C}^{\mathrm{fixed}}$ is a model object, specified in units of dollars per year. This object may be a variable, parameter or expression (calculation based on other components). Variable cost components c^{v} are indexed by timepoint (t) among all study timepoints ($\mathcal{T}$) and specified in units of dollars per hour. The term c_t^{v} is the element with index t from component c^{v}, i.e., a variable cost that occurs during timepoint t. The weight factor w_t^{year} scales costs from a sampled timepoint to an annualized value. For this study, we select one 24 hour day from each month of the year, so that the time points t specify actual hours. The weights multiply the individual days by about 30 such that the accounting reflects costs over an entire year.

Plug-in modules add components to the fixed and variable cost sets to represent each cost that they introduce. For example, the generator-building module adds the total annual fixed cost for all generators and batteries (capital repayment and fixed operation and maintenance) to the $\mathcal{C}^{\mathrm{fixed}}$ set, and the generator-dispatch module adds variable costs (fuel and variable O&M) for these facilities to $\mathcal{C}^{\mathrm{var}}$. The specification is generic so that models of different granularity may be considered depending on the needs of a particular problem and computational expense.

3.3.1.2 Operational Constraints

Power Balance: Specifies that power injections and withdrawals must balance during each time point. Injections are mainly output from power plants and battery storage, and withdrawals are mainly customer loads and battery charging. As with the objective function, plug-in modules add model objects to $\mathcal{P}^{\text{inject}}$ and $\mathcal{P}^{\text{withdraw}}$ to show the amount of power injected or withdrawn by each system component during each timepoint. For this study, production components were defined by the standard generation modules, and withdrawal components were defined by the standard electric vehicle model and a purpose-built responsive demand module.

$$\sum_{p^{\text{i}} \in \mathcal{P}^{\text{inject}}} p^{\text{i}}_t = \sum_{p^{\text{w}} \in \mathcal{P}^{\text{withdraw}}} p^{\text{w}}_t, \qquad \forall t \in \mathcal{T} \tag{3.11}$$

Dispatch: Power generation from a source (e.g., a power plant) must fall below its committed (turned on) capacity $W_{g,t}$ during time point t multiplied by a capacity factor $\eta_{g,t}$, that may vary with exogenous factors like solar radiation or wind speed.

$$P_{g,t} \leq \eta_{g,t} W_g, \qquad \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \tag{3.12}$$

Additional constraints further limit operation:

$$W_{g,t} \leq K_g, \qquad \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \tag{3.13}$$

$$d^{\min}_g W_{g,t} \leq P_{g,t}, \qquad \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \tag{3.14}$$

Equation 3.13 constrains the commitment choice to fall below the installed capacity K_g (possibly multiple identical units); equation 3.14 limits dispatch by a minimum-load constraint that applies to many power plants.

Minimum up and down times: The amount of capacity started up ($U_{p,t}$) or shut down ($V_{p,t}$) during each hour in each generation project is calculated via

$$W_{g,t} - W_{g,t-1} = U_{g,t} - V_{g,t}, \qquad \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \tag{3.15}$$

Additional constraints require that all capacity that was started up during an uptime look back window ($\hat{\tau}_g^{\mathrm{u}}$, defined for each project technology) is still online, and that all capacity that was shutdown during the downtime look back window ($\hat{\tau}_g^{\mathrm{d}}$) remains uncommitted.

$$W_{g,t} \geq \sum_{t'=t-\hat{\tau}_g^{\mathrm{u}}}^{t} U_{g,t'}, \qquad \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \tag{3.16}$$

$$W_{g,t} \leq K_g^{\mathrm{G}} - \sum_{t'=t-\hat{\tau}_g^{\mathrm{d}}}^{t} V_{g,t'}, \qquad \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \tag{3.17}$$

The variable $U_{g,t}$ is also used to determine startup costs for each plant (not shown).

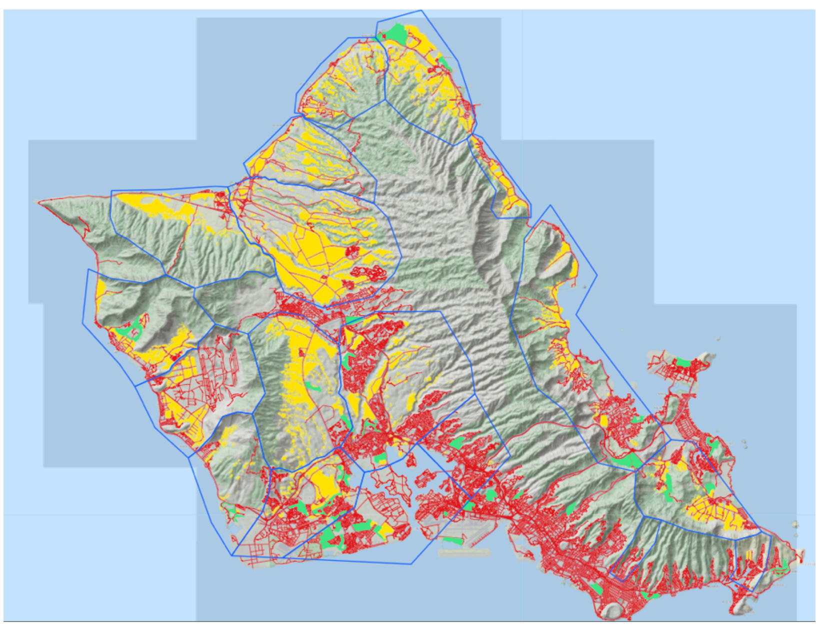
3.3.2 Oahu Configuration of Switch

Switch is configured based on Hawai'i's 2007 power system data, together with finely gridded, coincident, chronological wind and solar radiation data. Capital cost and fuel cost assumptions are based on Hawaiian Electric Company's recent Power Supply and Improvement Plan (`https://www.hawaiianelectric.com/about-us/our-vision`). Renewable resource potential is derived from screening available land resources as described below.

3.3.2.1 Utility-Scale Solar

Land available for utility-scale solar was restricted to parcels zoned for agricultural or country use, excluding Class A agricultural land per Hawai'i statute. This is conservative because it excludes a significant amount military land, and the military plans to install a considerable amount of solar. We also excluded land with a slope greater than 10%, land within 50 meters of street centerlines, and parcels with any directional dimension less than 60 meters. We assume fixed-panel photovoltaic installations use six acres per MW (AC) of capacity and that tracking photovoltaic installations use 7.5 acres per MW (AC) of capacity. These are roughly in the lower quartile of the national statistics indicated by the National Renewable Energy Laboratory (NREL)[6]. Fixed photovoltaic has a ground cover ratio of 0.68 and tracking systems have a cover ratio of 0.45. These assumptions affect the capacity factor when the sun is low. We then use NREL's PV Watts tool to calculate hourly output for each 4 km cell using irradiance data from the National Solar Radiation Database (NSRDB). The map of lands considered are shown in figure 3.4.

Figure 3.4: Land Available for Utility-Scale Solar



The map shows land that is assumed to be available for utility scale solar installations on Oahu given zoning and other technical and legal constraints (shown in yellow). Each area circled in blue is entered as a separate generation project in Switch, with different projects having different capacity limits and hourly production profiles. Red lines indicate roads.

[6]See http://www.nrel.gov/docs/fy13osti/56290.pdf.

3.3.3 Rooftop Solar

Rooftop solar potential was estimated from roof area from Google Map images. Visual review of many roofs indicates accurate identification. We assume 40 percent coverage of roofs, which is equivalent to 15 percent of roofs being flat with 70 percent coverage and 85 percent are sloped with 35 percent coverage. We estimate total capacity assuming 12 percent efficiency with 1000 W/m^2 irradiance (capacity = 120 W/m^2). Hourly output was estimated using PV Watts and the NSRD. figure 3.5 shows an image of rooftops on Oahu, including a closeup of the UH Mānoa campus.

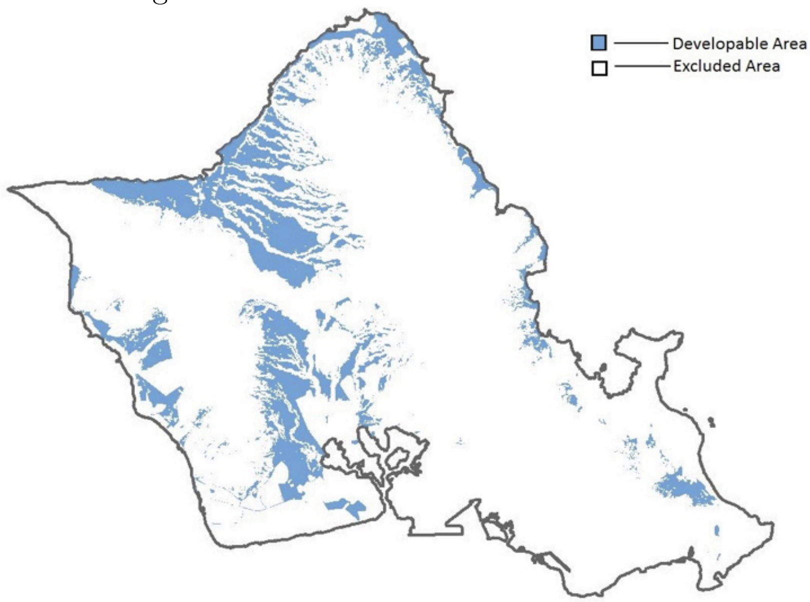
3.3.4 Wind Potential

On shore wind potential was estimated using a screening of available land similar to solar. Only land zoned for agriculture or country and not within 300 meters of other zones was considered. Slopes were restricted to 20 percent grade or less, and not within 30 meters of steep slopes, to eliminate narrow ridge tops and valleys. A map of areas potentially developable for wind is show in figure 3.6. We considered wind turbine density of 8.8 megawatts (MW) per square kilometer (km^2), which is conservatively less dense than the current Kahuku wind farm already installed on the island (12.9 MW/km^2), but on the high end of 5-8 MW/km^2 that is estimated by Denholm et al. (2009). Potential turbines were clustered by region into separate scalable projects. Hourly behavior of each potential project—its coincident potential capacity—is calculated based on historical meteorological modeling conducted for the Oahu Wind Integration and Transmission Study Corbus et al. (2010). For all practical purposes, there is an unlimited supply of off-shore wind potential with a high capacity factor of an estimated 43 percent, which enters the model as a single scalable resource.

Figure 3.5: Estimating Potential Rooftop Solar

The bottom image shows rooftop space islandwide (in lighted in yellow). The image on top shows a closeup of part of the Mānoa campus to demonstrate accuracy of rooftop identification.

Figure 3.6: Potential wind farm locations



The map shows land that is assumed to be available for on-shore wind development.

3.3.5 Time points and build scenarios

The model solves for a 30-year planning horizon and 12 representative days in each investment period, each representing a typical day from each month (the 15th), while constraining the model to achieve the state's 100 percent renewable energy goal by 2045 in the 100% scenarios. We also solve models that constrain generation to be purely traditional fossil fuels, plus a model that is unconstrained, and simply maximizes welfare (and minimizes costs) ignoring pollution externalities. The analysis we perform here is a single stage analysis in the sense that each scenario assumes all new assets are built at one point in time (i.e., 2045). Switch is designed to consider a series of investment windows so as to optimize a long-run plan or transition. However, because our focus in this paper is on the value of variable pricing, we chose to simplify this part of the problem so as to provide more clarity about the long-run tradeoffs of this critical policy choice. It is also possible to add more sample days to gain a fuller representation of the joint distributions of time, weather, supply and demand; this does not appear to change our results in a substantial way, but may be useful for fine-tuning an actual resource plan.

3.3.6 Equilibrium: Merging Switch with Demand

Iterations between Switch and the demand system were completed as follows. First, we solve Switch for a baseline load profile, which is connected to either actual 2007 loads or projected loads for 2045 (differences are discussed below). Tentative prices are derived as marginal costs (shadow values of the constraints specified in equation 3.11), and these are offered to the demand system. The demand system returns optimal quantities given these prices, and also reports Marshallian consumer surplus minus a fixed offset – i.e., the line integral of demand taken from baseline prices to offered prices. [7] Switch then minimizes the cost of serving the new quantities, sending new prices based on marginal costs. During successive iterations, Switch constructs a linearized demand system from the convex hull of the demand and total willingness to pay (consumer surplus plus total expenditure). In other words, it approximates total willingness to pay as a convex combination of willingness to pay from prior iterations (i.e., any linear combination of prior bids with total weight of 100%). During each iteration, Switch chooses a new system design to maximize welfare (willingness to pay minus cost) and offers new prices. This cycle repeats until there is no further improvement in total surplus from having new prices offered and receiving new bids.

This method is a Dantzig-Wolfe decomposition of the joint supply-demand problem Dantzig and Wolfe (1960). With this method, solutions from the supply problem, in which consumers are given quantities based on the linearized demand

[7] To find the correct competitive equilibrium in this iterative manner requires that we use Marshallian surplus rather than compensating or equivalent variation. Because nested-CES utility is well behaved and homothetic, this integral is not path dependent Takayama (1982). And because income effects are small, owing to the fact that electricity expenditure is a small share of income, this measure of surplus is also very similar to compensating and equivalent variation or money-metric utility. For this reason, we only report Marshallian consumer surplus.

function, represent a lower bound on surplus; solutions from the demand problem, in which consumers can choose any amount they want without changing prices, provide an upper bound on surplus. We stop iterating when the difference between these two measures is less than 0.1 percent of baseline electricity expenditure.

3.4 Cost assumptions and scenarios

3.4.1 Cost Assumptions

The inputs for the Switch model are based on Hawaiian Electric Company's Power Supply Improvement Plan (PSIP) and are summarized in table 3.2. The report lays out projected costs each year from 2016 through 2045, and we consider models with costs at each endpoint to show sensitivity of results to cost assumptions.

We summarize average capacity factors (normalized production potential) for the renewable sources in figure 3.7. In the optimization model, capacity factors for each project vary by hour. While projects with higher average capacity factors are more likely to be selected from the optimization routine, the timing of output also matters.

3.4.2 Scenarios

We solve the full model under a large number of scenarios to explore sensitivity of results to different assumptions (Table 3.3). Specifically, the scenarios span all combinations of the following sets of assumptions. Solving many scenarios also allows us to check internal consistency of results, which is useful for developing some confidence that the models converged correctly.

Most of the different sets of assumptions have been detailed above. We described the different interhour demand flexibilities in sections 3.2.2 and 3.2.4. Cost assumptions for 2016 and 2045 are summarized in table 3.2. Overall demand is likely inelastic, so we focus mainly on results with an overall demand elasticity

Table 3.2: Summary of Cost Assumptions

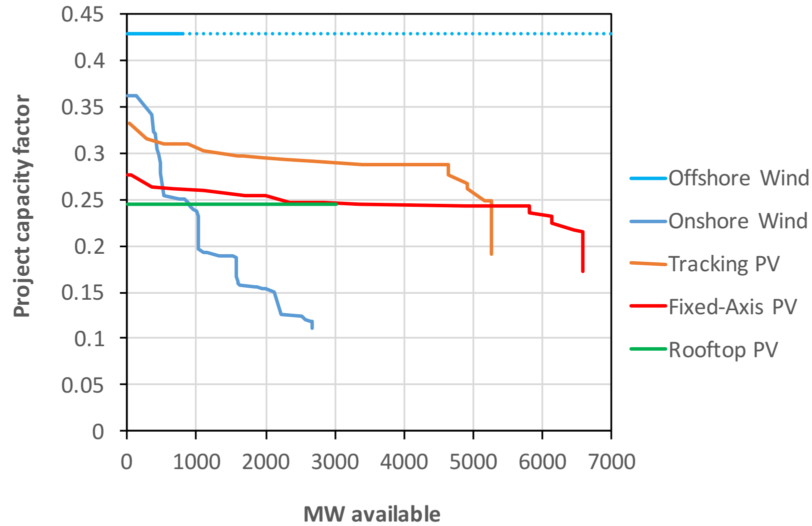
		Capital cost ($/MW)		Unit cost ($/MMBtu)		Op. & Maint.
Category	Description	2016	2045	2016	2045	($/MW/Yr.)
lightgray	lightgrayNew power generators					
	Combined Cycle Gas/Oil	1,653,242	1,415,952			17,452
	Central Tracking PV	2,856,257	1,680,388			22,970
	Distributed PV	3,650,295	1,511,097			-
	Diesel Barge	1,323,183	1,323,328			34,214
	Diesel MCBH	3,162,083	2,855,884			33,844
	Diesel Schofield	2,481,336	2,241,312			33,844
	Offshore Wind	6,205,598	3,882,934			96,710
	Onshore Wind	2,459,329	1,986,498			27,400
	Pumped Hydro	3,033,333	3,033,333			
lightgray	lightgrayStorage					
	Battery	484,283 ($/MWh)	146,639 ($/MWh)			
	Hydrogren Electrolyzer	1,596,797	697,014			
	Hydrogen Fuel Cell	990,562	528,787			
	Hydrogen Liquifier	42,997	42,997			
lightgray	lightgrayInputs for fossil power plants					
	Biodiesel			30.37	48.68	
	Coal			2.74	3.60	
	Diesel			10.48	32.50	
	LNG bulk			6.26	22.01	
	LNG container			10.52	14.38	
	LSFO			7.95	29.56	
	Pellet Biomass			14.00	14.00	

Note: Cost assumptions are derived from Hawaiian Electric Company's Power Supply Improvement Plan from December 2016. See `https://www.hawaiianelectric.com/about-us/our-vision`.

for electricity of 0.1 (the elasticity of substitution between electricity and all other goods). However, we do consider models with larger elasticities because some scholars may find these more plausible, and because new uses for electricity may arise that can make use of inexpensive electricity that would likely arise for significant stretches under high-renewable scenarios. New intermittent demands may be more elastic.

The two load profiles, actual 2007 and projected 2045, differ mainly in their degree of variability, including seasonality. Current demand tends to be considerably higher during Summer and early Fall, while loads that the Hawaiian Electric Company projects for 2045 are considerably flatter. Because seasonal variability may be more costly to manage than intraday variability, comparison of these scenarios provides some sense of this cost of seasonality. We do not have

Figure 3.7: Average output and potential capacity of renewable energy sources on Oahu



The graph shows the resource capacity of different potential sources of renewable energy, each ordered from highest average output (capacity factor) to lowest. For perspective, peak demand on Oahu is about 1000 MW. A project with a 0.25 capacity factor would produce an average of 25% of its nameplate capacity throughout the year.

Table 3.3: List of scenarios

Assumptions	Total Scenarios	Baseline Scenario	Other scenarios
Interhour demand flexibility	3	Optimistic	Pessimistic, Middling
Cost assumptions	2	HECO PSIP for 2045	HECO PSIP for 2016
Overall electricity demand	4	0.1	0.1, 0.9, 2.0
Electric vehicle share	3	50%	0.5%, 100%
Policy Objective	3	Fossil, 100% Renewable, Unconstrained	
Baseline load profile	2	Projected 2045	Actual 2007

a strong sense of why Hawaiian Electric Company believes the load profile will become flatter in the future, but we have augmented historical loads to match their projections for peak and average load in 2045. Because HECO reports a projected peak load of 1065 MW and average of 861.4, but the historical peak and average were 1249 and 955 (in 2007), the profile is flatter for 2045 than it is for 2007.[8]

Much of our discussion focuses on welfare differences between flat and variable, marginal-cost pricing, and those scenarios are crossed with all other sets of assumptions. Considering all combinations of the above scenarios yields $3 \times 2 \times 4 \times 3 \times 3 \times 2 \times 2 = 864$ scenarios. Computing time required to solve a single scenario can range from less than an hour for flat-price scenarios, to nearly two days for some of the dynamic scenarios where many different resources are on the margin. We used the University of Hawai'i's high performance computing facility with hundreds of state-of-the-art cores to solve many models simultaneously. Although space constrains us from reporting all individual scenarios, we have characterized many of them here, and have developed a website with drop down menus that will allow readers to explore details of any particular scenario (`http://www2.hawaii.edu/~mjrobert/power_production/`).

In addition to the above scenarios, we also solved models along a path wherein we constrain the percent renewable to a range of values between the least cost (unconstrained) portfolio and 100% renewable, holding all else the same. This allows us to trace out the social cost (loss in producer plus consumer surplus) of additional renewable energy under each set of assumptions. Note that we *do not* consider the external cost of pollution emissions. The idea is that whatever benefits society may glean from renewable energy above the minimum cost, such as reduced pollution externalities, ought to be weighed against these cost curves.

Welfare calculations consider changes in Marshallian consumer surplus (CS), producer surplus (PS), and charging costs for electrical vehicles (EV), which are treated separately but included in total CS. We also calculated CS for each

[8]We derived projected future baseline demand by multiplying the historical loads by 0.693 and adding 200 MW.

type of pseudo-customer, each having different interhour flexibility and base load profiles. CS changes are similar to compensating or equivalent variation, given the relatively small share of expenditure, so we do not report CV or EV. Producer surplus is the change in revenue minus total cost. Note that these calculations do not include fixed customer charges or rebates, which could be used to change the overall balance of welfare between customers and producers. For this reason, it may be more meaningful to focus on changes in total surplus and differences across pseudo-customers. Also note that we do not explicitly account for fuel savings that may derive from greater EV use. Comparison of low versus high EV scenarios are meant to show how EVs could change the value of variable versus fixed pricing, since EVs embody a potentially large block of flexible demand.

3.5 Results

To ease comparison of scenarios, results are reported as the difference between a particular scenario and a baseline scenario. In most cases, the baseline scenario, indicated by the boldfaced sets of assumptions in the list above, assumes fossil-based generation, future 2045 costs and projected load profile, flat pricing and an overall demand elasticity for electricity of 0.1 (the elasticity of substitution between electricity and all other goods). Note that under flat pricing scenarios, interhour demand flexibility has no bearing on the outcome. We choose this scenario as the baseline because we presume that it is the future that utilities envision in the absence of renewable energy. To make welfare calculations easy to interpret, we report these as percent differences from the baseline level of total expenditure on electricity.

3.5.1 Main Results

Table 3.4 reports the main results for scenarios with projected 2045 loads and costs. Comparing different rows from this table, one can infer the value of variable pricing under both fossil and high-penetration renewable systems. One can also infer the value of having more or less optimism about the degree of interhour flexibility of demand. Finally, we can see how much the projected cost trends favor renewables, by comparing current (2016) costs and projected costs in 2045.

We present a larger set of results graphically in figures B.6 and 3.10. The first figure shows the value of real time marginal cost pricing in comparison to flat pricing, all else the same. The second figure shows the social cost of a 100 percent renewable system (negative change in producer plus consumer surplus) against fossil and unconstrained baseline scenarios, all else the same.

To illustrate what a few scenarios look like in real time, figure 3.8 shows both consumption and production mixes by hour and season for middling demand flexibility, the scenarios that sit between the paired optimistic and pessimistic demand flexibility in table 3.4. For higher resolution depictions of all 864 s-cenarios, see the interactive website at: `http://www2.hawaii.edu/~mjrobert/power_production/`, which allows users to select desired scenarios from a series of drop down menus.

Finally, in figure 3.11 we show how the social cost of renewable energy rises as the share of renewable energy is gradually increased from the optimal portfolio (greatest social welfare, excluding pollution externalities) to 100 percent renewable. The graphs summarize a large number of scenarios and generally illustrate the value of variable versus flat pricing, the role of electric vehicles, interhour demand flexibility and overall demand elasticity, and current versus future technology assumptions.

The main observations that we can take from these results are:

- A small amount of demand-side flexibility is valuable. We can see this by observing that the pessimistic scenarios, with less than one sixth the amount of flexible demand as the optimistic cases, still benefit at least half as much from variable marginal-cost pricing as the optimistic scenarios.
- Under current costs, the unconstrained system is mostly fossil fuels (4 - 5.6 percent renewable), however under future projected costs, the unconstrained system is mostly renewable (73 - 80 percent). Increasing renewable energy shares 5-15 percentage points above these baselines tends to be inexpensive.

- Dynamic pricing in the unconstrained scenarios lowers costs while increasing the share of renewables. This value increases over time as the cost of renewables relative to fossil fuels declines, and renewable energy makes up a larger share of electricity in unconstrained scenarios.
- A 100 percent renewable system is projected to be less costly than a fossil system by 2045, but only under dynamic pricing.
- The value of dynamic pricing accrues mostly to consumers and may actually reduce producer surplus, while total surplus always increases with dynamic pricing. Adjustments in fixed charges could change this imbalance.
- Dynamic marginal cost pricing is considerably more valuable the greater the penetration of renewable energy, rising from about 2.6% under the baseline scenario with pessimistic demand flexibility, to 23.4 percent in a 100 percent renewable system with optimistic demand flexibility. Note that if the overall demand elasticity were larger, the value of dynamic pricing would also be greater, as high as 47 percent when $\theta = 2$ and the portfolio is constrained to be 100 percent renewable (results reported in the appendix).
- The production and consumption profiles indicate that in high-renewable scenarios, the value of the variable pricing mainly derives from considerably less use of batteries. In scenarios with more elastic overall demand, much greater value is realized by growing demand during low cost times when renewable energy is abundant.
- While variable pricing benefits more flexible demand types more than inflexible demand types, even inflexible demand types tend to benefit from variable pricing, and in some cases, nearly as much as flexible demand types.[9]
- Optimal dynamic prices vary a lot between days as well as within days, with many days having zero or near-zero prices nearly all day, and other

[9] This analysis accounts for the estimated baseline load profiles of more-flexible and less-flexible demand, but it *does not* account for individual heterogeneity of load profiles across customers. Residential customers, for example, may have little midday demand and high morning and evening demand, which would be more costly to serve.

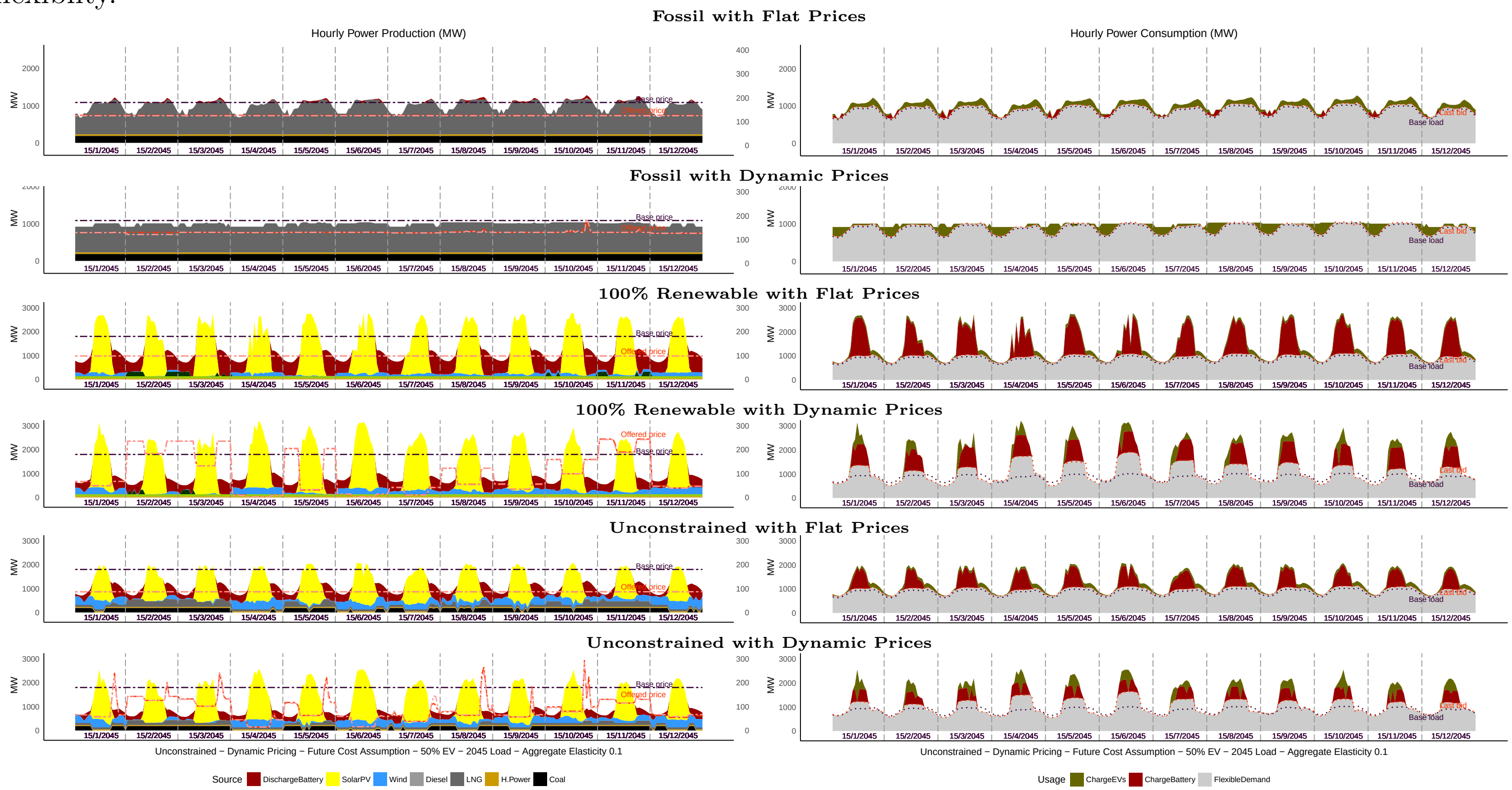
days having very high prices all day, even midday during peak sun. Put another way, storage and interhour substitution can arbitrage away much of the price differences between hours, but low-sun/low-wind days may have high prices all day.

Table 3.4: Main Results: Change in surpluses relative to baseline future fossil system with flat prices as a percent of baseline expenditure.

(1) Policy Objective	(2) Cost	(3) Demand Flexibility	(4) Pricing	(5) % Renewable	(6) Price ($/MWh)	(7) Mean Q (MWh/hr.)	(8) SD of Price ($/MWh)	(9) Δ CS (%.)	(10) Δ EV Cost (%)	(11) Δ PS (%)	(12) Δ TS (%)	(13) Δ CS Highflex (%)	(14) Δ CS Midflex (%)	(15) Δ CS Inflex (%)	(16) Δ TS Dyn (%)
Fossil	Current	Optimistic	Flat	4.12	87	944	0	33.6	-41.8	8.1	41.7	30.9	30.9	30.9	4.6
			Dynamic	3.99	62	980	2	58.9	-58.2	-12.6	46.3	51.8	51.8	51.8	
		Pessimistic	Flat	4.12	87	945	0	36.1	-37.2	5.1	41.2	31.5	31.5	31.5	4.1
			Dynamic	4.01	61	972	0	54.1	-57.4	-8.8	45.3	53.1	48.2	47.8	
	Future	Optimistic	Flat	4.27	124	906	0	Baseline							3.4
			Dynamic	4.31	131	900	3	-4.9	-2.7	8.4	3.4	-5.8	-5.8	-5.8	
		Pessimistic	Flat	4.28	126	904	0	Baseline							2.6
			Dynamic	4.25	107	912	0	8	-20.8	-5.5	2.6	14.8	6.3	5.4	
100% Renewable	Current	Optimistic	Flat	100	173	871	0	-38.9	36	-1.6	-40.5	-38.3	-38.3	-38.3	23.4
			Dynamic	100	128	959	86	-12.6	-15.5	-4.5	-17.1	3.1	-15.9	-25.7	
		Pessimistic	Flat	100	171	871	0	-37.1	33.8	-2.9	-40	-35	-35	-35	13.9
			Dynamic	100	137	931	96	-24.8	-14.9	-1.3	-26.1	6.4	-17.8	-28.9	
	Future	Optimistic	Flat	100	98	931	0	25	-30	-28.6	-3.6	21.2	21.2	21.2	13.7
			Dynamic	100	84	1047	75	39.3	-52.9	-29.2	10.1	43.4	30.9	26.2	
		Pessimistic	Flat	100	98	931	0	25.3	-29.1	-28.9	-3.6	22.4	22.4	22.4	8.5
			Dynamic	100	92	1016	80	33.9	-51.5	-29	4.9	45.2	31.7	27	
Unconstrained	Current	Optimistic	Flat	5.39	88	943	0	34.8	-23.7	6.9	41.7	29.7	29.7	29.7	4.6
			Dynamic	3.99	62	980	2	58.9	-58.2	-12.6	46.3	51.8	51.8	51.8	
		Pessimistic	Flat	5.63	82	949	0	38.3	-37.7	2.9	41.2	35.9	35.9	35.9	4.1
			Dynamic	4.02	61	972	0	53.4	-57.4	-8	45.3	53.1	47.8	47.3	
	Future	Optimistic	Flat	73	87	944	0	35.4	-35.7	-6	29.4	30.6	30.6	30.6	9.3
			Dynamic	80	71	994	32	45.5	-55.3	-6.7	38.7	45.7	37.5	34.4	
		Pessimistic	Flat	73	87	944	0	35.4	-34.7	-6.3	29.1	31.6	31.6	31.6	5.5
			Dynamic	79	79	976	39	39.3	-54.4	-4.8	34.6	47.1	36.3	32.4	

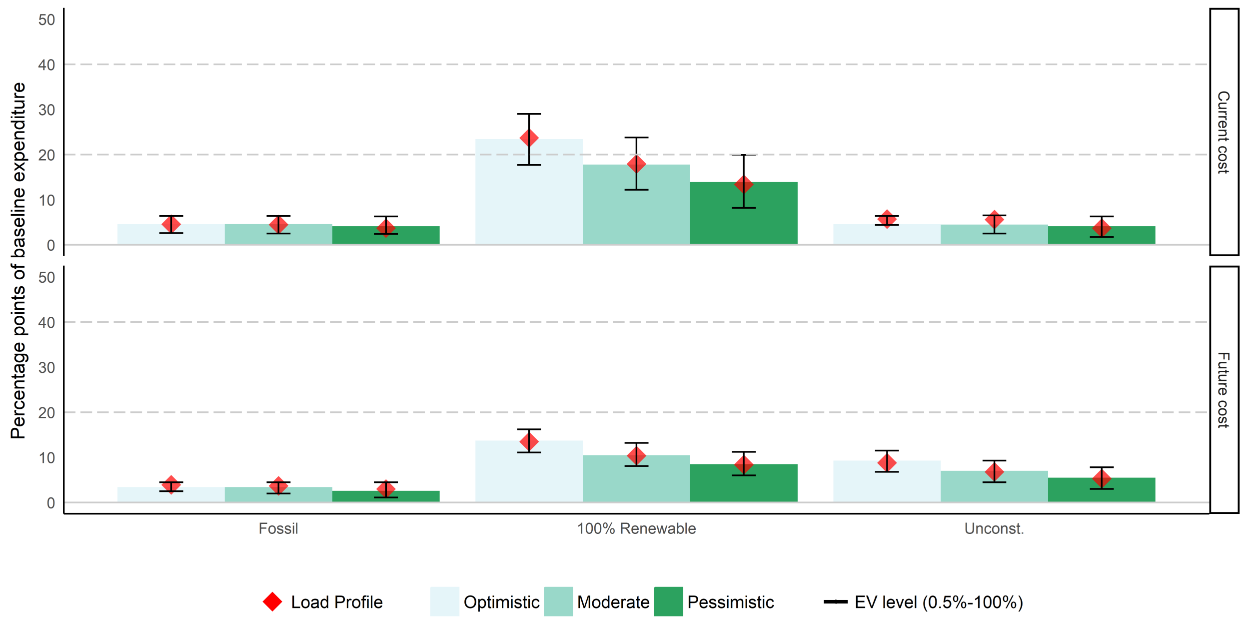
Notes: In all of the scenarios presented in this table, the overall demand elasticity for electricity (θ) equals 0.1, the baseline load profile is that projected for 2045, and electric vehicles are assumed to comprise 50% of the fleet. Each scenario (row in the table) is defined by assumptions delineated in the first four columns. The first column (Policy Objective) indicates exogenous constraints determined by policy: The Fossil scenario restricts any new installation of renewable energy, but is otherwise least cost; the 100% Renewable scenario reflects the intended outcome of the State's Renewable Portfolio Standard, and the Unconstrained scenario maximizes welfare without any constraints on the mix of power plants. The second column indicates whether current costs (2016) or the present value of future costs projected for 2045 from HECO's Power Supply and Improvement Plan are assumed. The third column indicates the degree of demand flexibility, as detailed in table 3.1. The fourth column indicates whether retail prices are flat or dynamic (time-varying and equal to marginal cost). The remaining columns summarize the outcomes of the conditionally optimized system: average price, average quantity, standard deviation of price, and changes in surpluses from the baseline case (fossil system, future costs, and flat pricing). All changes welfare are reported as the percent difference relative to the baseline level of expenditure on electricity. %ΔEV is simply the percent change in charging costs for electric vehicles from the base case. Note that ΔCS includes EV changes. We also examine changes in welfare for different demand flexibilities, which only matters for dynamic pricing scenarios. The last column reports the social value of dynamic pricing holding all else the same.

Figure 3.8: Hourly production and consumption profiles for several scenarios with middling interhour demand flexiblity.



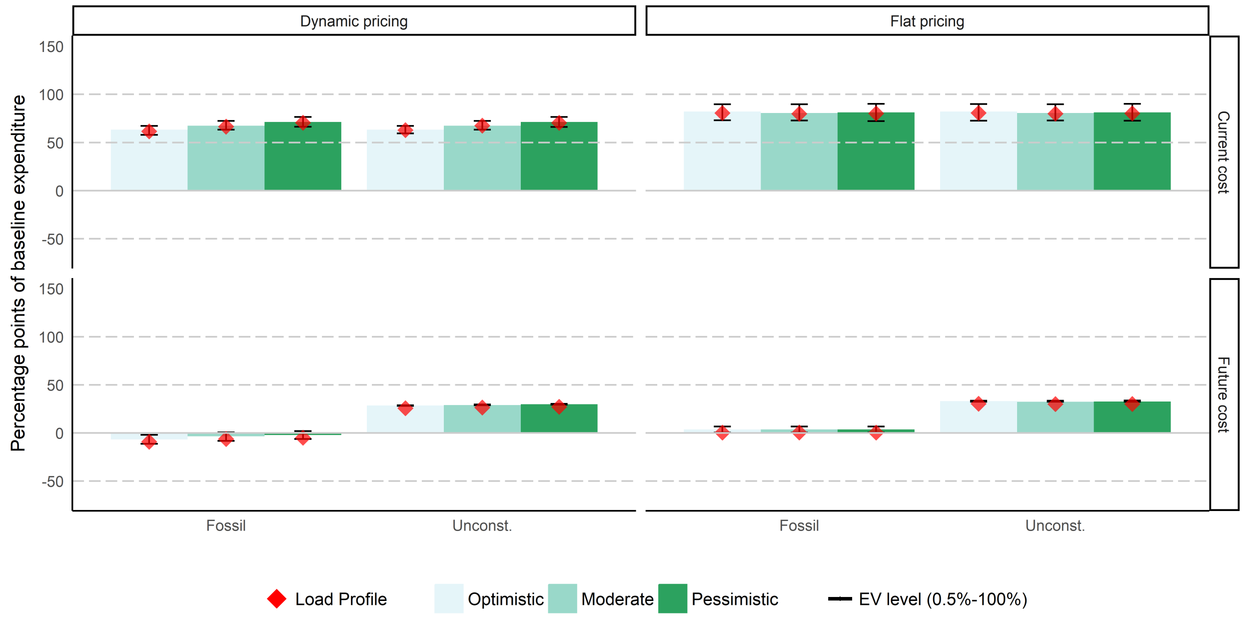
The scenarios presented above assume the middling scenario for interhour substitutability of demand, an inelastic overall demand elasticity for electricity equal to 0.1, a baseline demand profile projected for 2045, a vehicle fleet with 50% electric vehicles, and costs of production as projected for 2045 in HECO's Power Supply and Improvement Plan. The first two rows show fossil-fuel systems with flat and dynamic, real-time pricing; the next two rows show 100% renewable systems with flat and dynamic pricing; and the last two rows show the welfare-maximizing systems (resource unconstrained) with flat and dynamic pricing. Higher resolution graphs for all scenarios can be viewed at the website: `www2.hawaii.edu/~mjrobert/power_production/`.

Figure 3.9: Surplus gain from dynamic pricing under different policy, cost and demand flexibility scenarios.



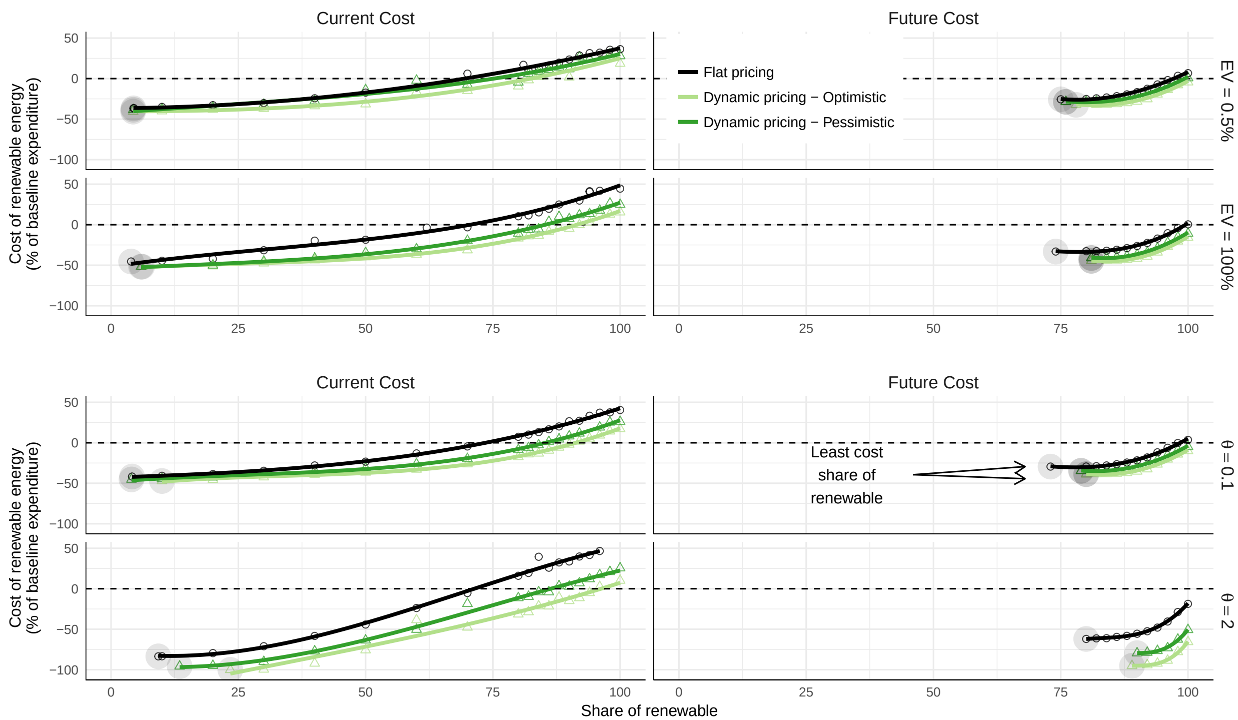
The graph shows the difference in total economic surplus with real-time marginal-cost pricing and total surplus when prices are flat, holding all else the same. Total surplus change is reported as a percentage of baseline (flat price) expenditure on electricity. The graph depicts all scenarios with an overall demand elasticity of 0.1; results for larger overall elasticities are shown in the appendix. The top row shows the value of variable pricing under current costs; the bottom row shows the value of variable pricing under projected future costs (2045). The horizontal axis shows the policy scenario: fossil, 100% renewable or unconstrained (maximum surplus, regardless of source). The bars show the baseline case with 50 percent electric vehicle fleet and 2045 load profile, the diamonds show the 2007 load profile, and the error bars show how results differ with 0.5 percent and 100 percent electric vehicles–more electric vehicles always increase the value of variable pricing.

Figure 3.10: Cost of 100 percent renewable energy system under different policy, cost and demand flexibility scenarios.



The graph shows the difference in total economic surplus with a 100 percent renewable system versus the baseline scenario given on the horizontal axis, holding all else the same. Total surplus change is reported as a percentage of baseline expenditure on electricity. The graph depicts all scenarios with an overall demand elasticity of 0.1; results for larger overall elasticities are shown in the appendix. The top row shows the value of variable pricing under current costs; the bottom row shows the value of variable pricing under projected future costs (2045). The horizontal axis shows the policy scenario: fossil, 100% renewable or unconstrained (maximum surplus, regardless of source). The bars show the baseline case with 50 percent electric vehicle fleet and 2045 load profile, the diamonds show the 2007 load profile, and the error bars show how results differ with 0.5 percent and 100 percent electric vehicles–more electric vehicles always increase the value of variable pricing.

Figure 3.11: The social cost of renewable electricity relative to a fossil future with flat pricing.



Each line shows the social cost—the loss in total economic surplus (PS + CS)—as the share renewable electricity rises above the least-cost share, holding all else the same. Social cost is measured as percent of expenditure in the baseline scenario, which is a predominantly fossil system with flat pricing in the year 2045. Thus, values less than zero imply a welfare improvement compared to using a conventional fossil system in the future (excluding externalities). Graphs on the left assume current (2016) costs, while graphs on the right assume future (2045) costs. Comparison of the top two rows shows the influence of electric vehicles (EV), contrasting the current fleet share of 0.5 percent EV with 100 percent EV. In the top two rows the overall demand elasticity is fixed at the baseline of $\theta = 0.1$. Comparison of the bottom two rows shows the influence of a more elastic demand ($\theta = 2$ versus $\theta = 0.1$), while holding the EV share fixed at 50 percent. In all graphs, black lines show the social cost with flat prices; dark green line show the social cost with variable prices and pessimistic interhour substitutability; and the light green lines show social cost with variable prices and optimistic interhour substitutability.

3.5.2 Supplementary results

In the appendix we report results from scenarios that are exactly like those reported in table 3.4, except we change individual assumptions that were held constant across all scenarios in the main results. We also replicate figures B.6 and 3.10 for different overall demand elasticities. These results mainly show that the value of dynamic pricing increases considerably, and the social cost of renewable energy falls, with a greater share of electric vehicle use and a higher overall demand elasticity.

3.6 Discussion

We developed the first integrated model of power supply, nonlinear demand, storage and reserves that simultaneously optimizes investment and chronological management of the system, with and without constraints on the share of renewable energy. The model is open source and generalizable to other settings with multiple nodes, transmission considerations, and multiple investment windows. We use this model to evaluate the benefits of variable pricing in comparison to flat pricing for fossil-based, unconstrained and high-renewable systems on Oahu, Hawai'i's most populous island. We find that variable pricing is considerably more valuable in high-renewable systems, that a large share of renewables will soon be optimal, even excluding externalities, and that the optimal renewable share is higher with variable pricing than it is with flat pricing.

Optimal power systems with a high share of renewables can use batteries and/or demand response to cost-effectively manage day-night and other short-term variations in supply. The larger challenge with intermittent renewables concerns seasonality and episodic or prolonged shortfalls in power generation. The optimized system manages these variations by striking a balance between overbuilding generation capacity for normal and resource rich times and, during resource poor times, using high-cost biofuels in traditional power plants and increasing prices to limit demand.[10] Unlike current fossil-based power systems wherein the main benefit of variable pricing comes from limiting peak demand, the benefits of variable pricing in high-renewable systems are multifaceted, lowering the cost of day-night balance, helping to limit generation capacity by staving off demand during resource lean times (not necessarily peak demand), and allowing greater social benefit from higher electricity use during resource rich times.

The last phenomenon—new uses of low-cost power—is a key source of value from variable pricing in high-renewable systems, especially when overall demand is more elastic. Although existing empirical studies suggest that demand is inelastic, we speculate that some of the inelasticity stems from the fact that retail pricing tends to be flat. It is hard to know how demand could evolve in an environment with long spells of essentially free energy. Currently cost-prohibitive energy uses, like desalination, may be both flexible in their timing and economic in high-renewable systems with long stretches of cheap power. Alternatively, new long-term, low-cost storage options may arise if appropriately incentivized. While flexible uses of low-cost power are speculative, they do seem plausible, and are what we have in mind in scenarios with higher demand elasticities. The benefit of more elastic demand is two-fold: it includes the extra surplus from more electricity consumption while making it easier to curb demand during resource lean times.

Some have suggested that the viability of low-cost, high-penetration renewable energy reflects Hawai'i's unique characteristics: the state is rich in wind and solar resources, but must otherwise import fossil fuels a great distance, making fossil fuels expensive relative to renewable alternatives. The unconstrained options also rule out additional installations of new coal-fired power plants. Still, the cost assumptions used in this analysis are fairly conservative, especially in light of rapid technological advancement in the last few years. By some esti-

[10]Switch also includes a hydrogen storage option, wherein excess generation produced in resource rich times is used to make hydrogen from water, which is then stored for fuel cell generation in resource lean times. This technology is not economic in most of our scenarios, but does show up in limited capacity in a few of them. Similarly, a pumped-water hydropower option that would make use of an existing reservoir is not economic in any of our scenarios.

mates, such as Bloomberg New Energy Finance and Lazard,[11] current renewable energy and battery technology costs already rival Hawaiian Electric Company's projections for 2045 Lazard (2017).

At the same time, renewable energy in Hawai'i is in some ways more challenging than other locations, due to its extreme isolation. In continental regions, which have much more connectivity, transmission provides another, potentially lower-cost method of managing intermittency challenges, as well as transferring renewable power from areas rich in renewable resources to areas that are renewable energy poor. The modeling framework presented here can be used to assess the substitution possibilities between transmission and demand response, and generally optimizing high-dimensional chronological power systems in a realistic way. Solving such a model would be computationally expensive, perhaps two orders of magnitude more expensive that our model of the island of Oahu, but potentially feasible with solution algorithms that could subdivide the larger problem and thereby make use of modern parallel computing.

We believe these results provide credible evidence that high-penetration renewable energy is viable at reasonable economic cost in many places soon. The low cost of renewable energy greatly strengthens the case for real-time dynamic pricing options at the retail level.

[11] See `https://about.bnef.com/blog/` and `https://www.lazard.com/perspective/levelized-cost-of-energy-2017/`

Chapter 4

The Response of Consumption to Fuel Switching: Panel Data Estimates

Dirty fuel used in cooking has long been associated with poor health and low productivity. Nonetheless, almost half of the world population is still using it. The desirability to switch to a cleaner fuel depends critically on the extent to which the switching changed households consumption. Policies and interventions that targeted on improving household's access to clean cooking energy, including the seventh United Nation's Sustainable Development Goal, have been aggressively trying to tackle this issue. Poor knowledge concerning energy use, consumption pattern, and behavioral response from fuel transition have been translated into uncertainties when formulating this intervention.

Do households improve their standard of living – their consumption – as they switch to more cost effective and cleaner fuel? Using the Indonesia fuel conversion program, I aim to evaluate household response to fuel switching. In 2007, the government of Indonesia ambitiously aimed to encourage more than 70% of all households in the country to switch from kerosene to LPG, a relatively clean, efficient and cost-effective fuel compared to kerosene. The main purpose of this program is to reduce kerosene subsidies, as the government spent almost ten billion USD in 2006 for it. On the consumer side, based on laboratory experiments, one litre of kerone has an end-use energy equivalence of 0.6 kg LPG, under various cooking condition. This program has been successful in increasing the proportion of household who use LPG from 9% to 46%, and decreasing the proportion of household who use kerosene from 42% to 12% (IPUMS, 2013). The reduction on the cost of subsidizing kerosene is claimed to save almost USD 2 billion by May 2010 (Budya and Arofat, 2011).

To conduct this analysis, I use the difference-in-differences estimation strategy on four waves of the Indonesia Family Life Survey. The identification comes from the random variation in the timing of implementation of the program. I focuses on the kerosene consumption, fuel expenditure, utility bills, and other nondurables expenditure as they are likely influenced by households' cooking fuel directly. While households in the treated districts may differ systematically from households in the untreated districts, I show that, within households, expenditure is very similar over time prior to the program. The program is also not correlated with households' main characteristics, which give some indication that there are no subsequent changes that might lead to spurious results. Note that the estimation captures partial equilibrium effect as it only captures the changes in spending correlated with the program timing. The ultimate impact of the program on aggregate consumption could be higher or lower than my estimation, due to multiplier effects and possible changes in prices.

I find that households reduce their kerosene consumption up to 100%. Household utility bills are reduced by 40%, 1.19 USD per month, on average. This response is statistically and economically significant, especially for the poor households. Fuel expenses takes about 30% of household utility bills, on average, with substantial heterogeneity across income brackets. This estimate is consistent with several small surveys conducted after the program (Budya and Arofat, 2011; Andadari et al., 2014). I do not find any response to other nondurable expenditures which provides some evidence that, in this setting, consumption does not change in response to expected variations in fuel expenditure. Although this paper does not test any particular theoritical model, the results support rational expectation life-cycle theory which implies no spending response to a predictable change in anticipated changes in resources.

This paper is structured as follows. Section I describes the policy context of energy transition and its potential economic impact. Section II describes the IFLS data and main baseline characteristics, and Section III sets my empirical methodology and relevant validity test. Section IV presents the main results regarding household's response to the fuel switching, and how it differs across households' characteristics. Section V concludes.

4.1 Policy Context

How clean energy transition influence household total energy consumption? Does household transition to a more cost effective cooking fuel reduce their total energy expenditure? Do households smooth their consumption during the transition. These questions are fundamental in designing interventions that support a sustainable energy transition, considering that cooking fuel plays an important role in household's well being (Duflo et al., 2008).

The Seventh Sustainable Development Goal emphasizes on affordability, reliability and sustainability of modern energy for all by 2030. In 2014, the access to clean fuels has climbed slowly from 51 per cent in 2000 to 58 per cent in 2014 (Economic and Council, 2016). Today, in the world, there are still more than 3 billion people, mainly in Asia and sub-Saharan Africa, are still cooking without clean fuels and more efficient technologies. Policy reports have increasingly associated the use of dirty fuel with mortality and burden of disease (Zhang and Wu, 2012). Hence, policy makers, donors, and international organization have put this issue into their priority.

In 2005, more than 80% of household in Indonesia is still using dirty fuel for cooking, mainly wood fuel and kerosene. Government highly subsidizes kerosene, known as a cleaner fuel compared to wood fuel, to incentivice households to shift from wood fuel. Inevitably, it triggers unintended use of the fuel by reselling the fuel to industries or abroad. Indonesian Government started to subsidize other cleaner, LPG, and limit the supply of kerosene.

4.1.1 Large Scale Fuel Switching

Indonesia, the worlds fourth-most-populous country, with 243 million people, has been subsidizing the retail price of cooking fuels since 1967 (Dillon et al., 2008). As in 1980s Indonesia's oil production is high, fuel subsidies were affordable. But domestic energy consumption of Indonesia has surged by more than 50% over the past decade. Moreover, the increase in global our prices has increase the subsidy cost more than 4 billion USD in 2007. In response to this, in 2007, Indonesian government launched Kerosene to LPG Conversion Program [1].

The main purpose of this conversion program was to reduce the amount of government subsidy on kerosene.[2] The cost to provide LPG is lower than kerosene[3] and its infrastructure is also more available compared to other alternatives, such as natural gas and electricity. The government aimed to convert 73% of households who use kerosene[4] to LPG. Households who use kerosene primarily and have not use LPG before were eligible in the program. They would received a free LPG stoves along with one 3-kilo LPG cylinder. Having this specific type of cylinder makes them also eligible to refill it under subsidized price. The implementation is gradual over time and homogenous across districts. The Ministry of Energy and Mineral Resources selects the treated districts in a given fiscal year based on each district's level of kerosene usage, LPG infrastructure readiness, location and size of the area. Seven years later, there is a decrease in the percapita fuel expenditure but only among those that got the program (Figure 4.1). As can be seen, the distribution for households in the treatment group and in the control group are very similar prior to the program. After the program, there is a big shift to the left which reflects the reduction in the fuel expenditure.

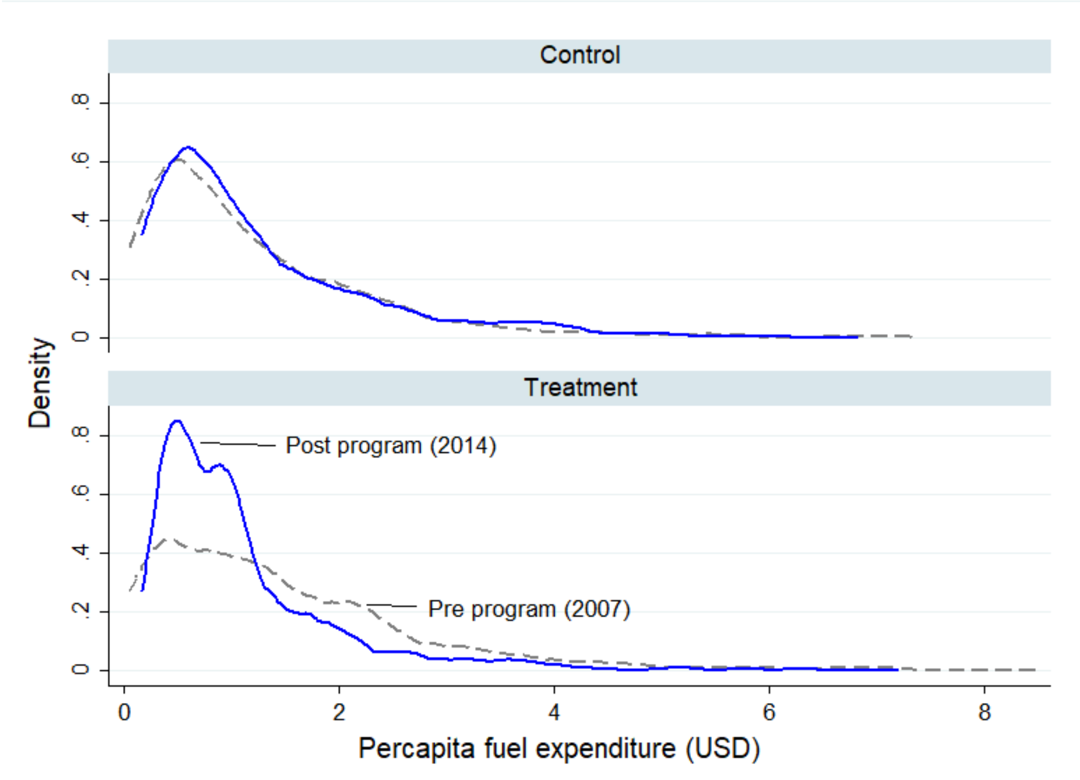
[1] `http://prokum.esdm.go.id/perpres/2007/perpres_104_2007.pdf`

[2] Some other purposes and the detail of the program are discussed in (Budya and Arofat, 2011).

[3] Subsidizing kerosene cost 25% (0.17 USD/liter) higher than subsidizing LPG (see Andadari et al. (2014)).

[4] 42 millions from 57 total households in 2007

Figure 4.1: Density of percapita fuel expenditure before and after the program



Notes: This figure shows the density curve of percapita fuel expenditure for treatment and control group before and after the program. The treatment group is households who reside in the district that get the program before 2011 and the control group is households who reside in the district that get or not yet get the program after 2011.

4.1.2 Potential Economic Impact of Fuel Switching

Existing studies on the impact of energy transition has largely focused on health issues, as burning dirty fuel produces indoor air pollution that has adverse impact on health and productivity (Duflo et al., 2008; Graff Zivin and Neidell, 2012). Those studies largely based on observational studies. Indeed, we have very limited evidence on the causal impact of fuel switching, especially on economic outcomes such as energy consumption pattern, adult labor market productivity, child school attendance, and medical cost. For example, when household members use more efficient fuel for cooking, they might cook faster and burn less fuel. They would consume less, thus have lower total energy expenditure. They might also consume more, considering that now cooking is more convenient. If there is any changes in energy expenditure, will households tend to smooth their consumption by spending the extra money for some other consumption. Some other possibility is that using cleaner fuel also save time from fuel collection, cleaning up kitchen and stove, which then enable households' hours available towards income-generating purposes. These potential effects are mixed and difficult to disentangled in a structural framework. Hence, this paper focuses on the empirical evaluation of the average treatment effect on household consumption due to fuel switching policy.

Relevant studies measuring reactions to changes in resources are usually linked to consumption smoothing and the permanent income hypothesis. The program is implemented gradually and goes through various stages and thus households certainly aware of its occurrence. Given that there are many ways in which households are likely to have responded to change in household energy mix, it will be difficult to predict with much confidence what the combined impact in household consumption is likely to be in the presence of any subsequent multiplier, and how those impacts are likely to vary across socio-economic and demographic groups. In the absence of empirical evidence in the past studies, this paper focuses on households' consumption smoothing over an anticipated change in energy mix.

Many studies have put a lot of emphasize on wood fuel. Kerosene is the only cooking fuel product consumed by the low-income households in urban population, and the second after wood in rural population. While the cost of subsiding it is high, it is claimed as an ineffective social policy as there are many cases of unintended use of kerosene subsidy (Mills, 2017). On the health side, WHO is no longer classifying kerosene as clean fuel, and discourage the use of it instead (WHO et al., 2012) as burning kerosene has been found to be as bad as wood fuel (Saksena et al., 2003). Hence, this study fills the gap in the literature by discussing the impact of a decreasing use of kerosene and an increasing use of LPG.

4.2 Data and Summary Statistic

4.2.1 IFLS

I employ four waves of the Indonesian Family Life Survey (IFLS), a longitudinal survey carried out by the RAND corporation (Thomas et al., 2012) that were carried out in 1997, 2000, 2007, and 2014 respectively. IFLS is known as one of the best longitudinal data with a very low level of attrition due to its successful follow-up rates despite of the mobility of the respondents and it represents 83% of the Indonesian population living in 13 of out of 26 provinces. The data contains a great amount of information at individual, household and community level on a large array of economic, social and labor supply characteristics. I focus on consumption and expenditures measurements to measure the well being of households.

4.2.1.1 Consumption measurements

Firstly, I use quantity of kerosene from the recent purchase and the unit price of kerosene from the last purchase as the outcome variables, considering that the program has a direct influence in kerosene availability in the market. The survey asks "within one month recall period, the last time you purchased kerosene, what was the quantity you purchased?". Note that this variable does not capture the total quantity of kerosene use by households, but rather the sum of one time purchase at one time by all household's members, during last week preceding the survey.

Then, to look at how households' response to the program, I use expenditure on nondurables in a given period as a preferable measure of consumption, following Browning and Lusardi (1996). The outcome variables are a series of subcategories of monthly nondurable expenditures: (1) utility bills, which includes fuel, electricity, water and telephone expenses; (2) food, which includes food/products bought/consumed by all the members of household, food consumed away from home, and cigarettes and tobacco; (3) other strictly nondurables[5], excluding item (1).

Changes in utility bills or food expenditures might alter the marginal utility of consumption from other nondurable goods. If this is true, then the effect on nondurable expenditure is For example, households invest in This would be true if, change I exclude those to allow separate analysis for each component. It is reasonable to assume that changes in expenditures for food and utilities is inelastic and separable in utility from other consumption. In addition, these component account for a significant share of a typical household budget, thus the variation is economically meaningful. Note that fuel expense in the utility bills is a different category from fuels for transportation. All expenditures are in monthly and percapita real terms (adjusted with 2007 Consumer Price Index).

IFLS uses an up to one month recall period, in which households was asked about their last purchase history for high frequency items such as food and fuel, and up to a year for low frequency expenditure such as health. The respondent is asked to recall the food items purchased, self-produced, or received from another source during the last week. For expenses like utilities, transportation, and domestic services, the reference period is the past month. The reference period for medical and education expenditures is the past year. The question is formulated as follows: "How much money was spent for non-food items during the past month?" Responses are collected based on the month of interview. This is not a trivial issue given the importance of seasonal effects in consumption processes. Hence, for robustness, I include a model that uses month-year fixed effects.

4.2.2 Program Implementation

Ministry of Energy and Mineral Resource decides the order in which districts are treated. Pertamina, a State-Owned energy company, implements the program based on the given order. It is noted that the program is targeted based

[5]This category follows Browning and Lusardi (1996), which excludes apparel, medical services, and education expenses

on the district's kerosene consumption which might be correlated with some other district's characteristics which then lead to household sorting. While non-randomization is acknowledged, my empirical analysis will focus on comparing households in district that are treated to other initially similar households in districts that have not yet treated that might otherwise behave in the similar way. Table 4.1 shows total households in the sample and number of unique districts in the sample based on the program year. Later in the analysis, I classify the treatment group is households who reside in the district that get the program before 2011 and the control group is households who reside in the district that get or not yet get the program after 2011. For robustness checks, I consider some alternative for the control group.

Table 4.1: Total sample by program implementation year

	Program Implementation Year		
	2007-2010	2011-2013	>2013
Total Households	16,226	2,908	960
Total Districts	147	39	9

Source: Pertamina

4.2.3 Average Household Characteristics and Baseline Differences

Table 4.2 shows the key descriptive statistics of the data before the program. I report the average values and its standard deviation of households' characteristics in the control group, weighted with the survey weights, in column 1 and 2. In column 3 and 4, I report the average values and its standard deviation of households' characteristics in the treatment group, weighted with the survey weights. In column 5 and 6, I report the within-household difference between the average values of the treatment and the control households at baseline, controlling for household fixed effects and province-year dummies.

Primary cooking fuel. On average at the baseline years, about 30%-43% of households are using kerosene as their main cooking fuel, while 45%-68% of households are using wood as their main cooking fuel. There are very few households use either LPG or electricity. The trend to use these fuels between treatment and control group are very similar as shown in column 5.

Households characteristics. Households size is three on average, with total monthly expenditure around 70 USD. About 40% is spent on food and 8% is spent on the utility bills. Total working hours for all households members are around 23 hours per week. Average last year income, an estimate for household members that worked last year and for whom respondent knew earnings of last year, is 300 USD, or 25 USD per month. Average yearly income during the survey year is calculated from reported monthly salaries, about 130 USD, which are consistently about two of the fifth of reported last year income. More than 80% of households own their house and do not move.

4.3 Empirical Methodology

I use difference-in-differences estimation strategy to exploit variation across time of program implementation on household level panel data, following Eq. 4.1.

$$C_{hrt} = \beta_{1h} + \beta_{2t} + \beta_3 P_{r2014} + \beta_4^{'} X_{ht} + \epsilon_{hrt} \tag{4.1}$$

where h indexes households, r indexes district, and t indexes year of survey, C is household consumption or their log; α_h, β_{1c} are household, and time fixed effects. Following the literature, I add 1 if the dependent variable is zero before taking log transformation. X_{ht} is a set of covariates that capture household characteristics (age, family size, interview month and year). P_{r2014} is a dummy of the program implementation, that is the interaction between treated district and year of 2014. Using a dummy variable for the program implementation guards against measurement error. I use ordinary least squares and cluster the standard errors by district to allow for heteroskedasticity and serial correlation in within district as the implementation of the program is varied by district.

Key coefficient of interest is β_3 which measures the average response of household consumption to the program implementation. This reduced form effect

Table 4.2: Baseline Household Characteristics Before the Program

	Control group (N=2,930)		Treatment group (N=12,199)		Within-HH differences	
	Mean	SD	Mean	SD	Mean	SE
	(1)	(2)	(3)	(4)	(5)	(6)
Primary cooking fuel:						
Electricity	0.00	0.05	0.00	0.07	0.02**	(0.01)
LPG	0.01	0.11	0.11	0.32	0.03	(0.03)
Kerosene	0.29	0.46	0.43	0.50	-0.02	(0.05)
Wood	0.68	0.46	0.45	0.50	-0.02	(0.04)
Percapita kerosene (litre)	1.68	7.32	1.34	6.03	-0.12	(0.46)
Kerosene price (USD)	0.2	0.53	0.16	0.3	-0.11	(0.20)
Household characteristics:						
Husband age	36.90	22.06	38.82	21.69	-0.34	(1.85)
Wife age	41.00	14.61	41.50	14.94	-0.55	(1.26)
Household size	2.92	1.32	3.01	1.34	-0.03	(0.11)
Number of adults	0.33	0.56	0.29	0.52	-0.10	(0.07)
Number of children	2.41	1.17	2.52	1.22	-0.02	(0.10)
Number of elderly members	0.02	0.15	0.02	0.16	-0.00	(0.01)
Use electricity	0.84	0.36	0.92	0.27	-0.14*	(0.08)
Own house	0.86	0.34	0.87	0.34	0.00	(0.04)
Have fridge	0.16	0.36	0.17	0.37	0.02	(0.06)
Boil water to drink	0.83	0.38	0.93	0.26	-0.03	(0.07)
Did not move	0.75	0.43	0.88	0.33	-0.03	(0.18)
Percapita total expenditure (USD)	72.13	315.13	71.42	381.76	17.57	(17.30)
Percapita non-durables (USD)	57.25	284.38	58.47	360.54	18.09	(15.49)
Percapita food exp. (USD)	31.04	25.86	28.99	49.40	3.28	(3.06)
Percapita utility bills (USD)	6.58	124.50	10.87	159.93	11.70	(12.56)
Working hours per capita/week	23.08	18.95	23.41	19.23	-5.06**	(2.13)
Percapita last year income (USD)	302.99	431.12	281.37	617.36	-99.95	(68.15)
Percapita this year income (USD)	129.10	296.46	138.46	464.67	-11.01	(24.51)
Head of household:						
Female	0.16	0.37	0.15	0.35	-0.03	(0.03)
Uneducated	0.12	0.32	0.13	0.33	0.02	(0.02)
High school educated	0.81	0.39	0.81	0.39	-0.00	(0.03)
Diploma or higher	0.07	0.25	0.06	0.24	-0.02	(0.01)
Worked last year	1.21	0.61	1.22	0.63	0.07	(0.08)

Notes: All regressions use the sample prior to the program. Control group is households living in the districts that get the program after 2011 (less than three years). Treatment group is househoolds living in the district that get the program during 2007-2010. In column 1 and 2, I report the average values and its standard deviation of control households at baseline. In column 3 and 4, I report the average values and its standard deviation of the treatment households at baseline. Each row in column 5 and 6 is the estimated differences from a regression of each household characteristic on an indicator variable whether the households are in the treatment group, controlling for household fixed effects and province-year dummies. The standard error is clustered by district. 1 USD = Rp 13,000.

contains two components: substitution effects and income effects. Substitution effects arise when the prices of kerosene increase due to removal of the subsidy, and households will substitute towards other fuel alternatives as they become relatively cheaper than kerosene. Income effects arise when the lower effective price for other alternative fuels increases household's purchasing powers, leading to a further increase in consumption of those alternative fuels (assuming it is a normal good) and other normal goods consumption.

The main empirical challenge is that households in the treated districts may differ systematically from households in the untreated districts, that is the timing of program implementation might have been associated with unobserved factors that otherwise influence households consumption trend in the targeted districts. To address this issue, first, I show that the pre-implementation trends in consumptions between treatment and control groups are very similar. In Table 4.3, I show regression coefficient of each outcome variable on the district and year dummies. Table A.1 in appendix confirms that the results are very similar, with or without household fixed effects. In other words, households in the treatment and control groups are very similar before the program on their percapita kerosene quantity, nondurable expenditure and their utility bills. They also face similar price of kerosene.

Secondly, a probit for being in the treatment group against a variety of observable characteristics did not reveal any strong systematic correlations (Table 4.4). This result is consistent with (Andadari et al., 2014; Imelda, 2018) which study the same program. They show that the program induced by the program has been largely independent of household characteristics. Although households in the treatment group shows that they are more likely to have less household members, this is actually driven by the increase in household members in the control group. There is also a weak correlation that households with less uneducated members are likely to be in the treatment group, the coefficient are very small, 5%. Overall, there is little evidence on any systematic difference between households in the treatment group and the control group. For the robustness checks, I include these control variables and the main conclusion stays.

To some extent, the results from Table 4.3 and Table 4.4 help to address

Table 4.3: Test of parallel time trends

	(1) Strictly non-durables	(2) Food	(3) Utility bills	(4) Trans-portation	(5) Rotating savings	(6) Household expenses	(7) Personal toiletries
Panel A							
ProgramX2007	0.261*	0.128	0.123	0.728	0.066	0.211	0.291
Standard error	(0.142)	(0.109)	(0.294)	(0.827)	(1.036)	(0.215)	(0.312)
Obs.	15,058	15,097	15,097	15,097	15,097	15,097	15,097
R-squared	0.642	0.599	0.579	0.505	0.612	0.407	0.448

	(8) Servants' wages	(9) Sweeptakes	(10) Monthly expendi-ture	(11) Durables	(12) Medical	(13) Last year income
Panel A						
ProgramX2007	0.265	-0.002	0.287**	1.017***	-0.542	0.418
Standard error	(0.197)	(0.094)	(0.144)	(0.385)	(0.433)	(0.531)
Obs.	15,097	15,097	14,995	15,097	15,097	15,129
R-squared	0.499	0.353	0.666	0.524	0.455	0.548

Sample is prior to the program. All regressions include district fixed effects and month-year dummies. The standard error is clustered by district.

Table 4.4: Is the program correlated with the observables?

	(1) Husband age	(2) Wife age	(3) Household size	(4) Number of adults	(5) Number of Children	(6) Use electricity	(7) Own house	(8) Have fridge	(9) Boil water to drink
ProgamX2014	-1.25	-1.32	-0.36***	-0.29***	-0.01	-0.07	0.01	0.01	-0.01
	(1.860)	(1.039)	(0.107)	(0.099)	(0.070)	(0.054)	(0.023)	(0.049)	(0.064)
Obs.	20,094	20,094	20,094	20,094	20,094	20,094	20,094	20,094	20,094
R^2 stat	0.573	0.570	0.506	0.470	0.302	0.576	0.568	0.566	0.460

	(10) Did not move	(11) Percapita food exp.	(12) Percapita income	(13) Female	(14) Uneducated	(15) High school educated	(16) Diploma or higher	(17) Worked last year
ProgamX2014	-0.01	-1.88	-23.50	-0.00	-0.05**	0.03	0.02	-0.00
	(0.121)	(2.578)	(93.590)	(0.036)	(0.024)	(0.038)	(0.021)	(0.085)
Obs.	20,094	20,051	20,094	20,094	20,094	20,094	20,094	20,086
R^2 stat	0.424	0.364	0.451	0.598	0.671	0.671	0.757	0.455

Each column reports the estimated differences from a regression of each household characteristic on an indicator variable whether the household is in treated region, controlling for household fixed effects and province-year dummies. Column 1 - 13 report the main household characteristics. Column 14 - 17 report the head of household characteristics. The standard error is clustered by district.

some concern about possibly unobserved shocks that might be correlated with household's consumption. Thus, in further analysis, I consider that the control group as a valid counterfactual for the treatment group in the absence of the program, conditional on household fixed effects, district-year fixed effects, and the other time-varying household characteristics.

4.4 Estimated Impacts of Fuel Switching

I begin the analysis by estimating the average program effect using full sample. Using different timing of the program, I refine my identification strategy subsequently using alternative treatment and control groups by exploiting: (1) comparing only early treated districts with the untreated districts, (2) comparing only the late treated districts with the untreated districts, (3) comparing only treated districts.

4.4.1 Variation across all households

The program effect on quantity and price of kerosene. Table 4.5 show that per-capita kerosene quantity in the last purchase one month preceding the interview (column 1-4) and log kerosene price per litre (column 5-8). After the program, households no longer buy kerosene and kerosene price is increased up to 70% due to the program. Note that the sample is significantly reduced to 15,193 observations for the kerosene quantity and to 9.169 for kerosene price, due to missing values.

The program effect on primary cooking fuel. I present the effect of the program on household's primary cooking fuel choice in Table 4.6. Column 1-4 indicate the independent variable, which is a dummy variable of household's cooking fuel. It shows that the program significantly increases the probability of using LPG and reduces the probability of using kerosene by 50%. The program has no effect in the use of electricity and wood fuel. The magnitude is slightly higher compared to the estimates in (Imelda, 2018), considering that it accounts for household fixed effects.

Table 4.5: Effect of the program on kerosene quantity and price

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Percapita Kerosene Quantity (litre) Mean: 0.93 litre per one time purchase				Log (Kerosene Price) Mean: 0.19 USD/ litre			
ProgamX2014	-1.560***	-1.408***	-1.409**	-1.831***	0.338***	0.263***	0.277***	0.337***
	(0.499)	(0.350)	(0.586)	(0.683)	(0.033)	(0.026)	(0.045)	(0.078)
Observations	15,153	15,153	15,153	15,153	9,136	9,136	9,136	9,136
R-squared	0.038	0.023	0.356	0.354	0.148	0.146	0.579	0.570
District FE	Y				Y			
Prov. X Year FE		Y	Y			Y	Y	
Household FE			Y	Y			Y	Y
Interv. Month FE				Y				Y

Each column reports the estimated differences of percapita kerosene quantity in the last purchase one month preceding the interview (column 1-4) and log kerosene price per litre (column 5-8) due to the program, controlling for household fixed effects and province-year dummies. The standard error is clustered by district.

Table 4.6: Effect of the program on primary cooking fuel

	(1)	(2)	(3)	(4)
	Primary cooking fuel:			
	Electricity	LPG	Kerosene	Wood
ProgamX2014	0.00	0.45***	-0.50***	0.05
	(0.00)	(0.07)	(0.07)	(0.04)
Observations	20,094	20,094	20,094	20,094
R-squared	0.26	0.68	0.61	0.70
Treated Mean	0.00	0.27	0.32	0.40

Each column reports the estimated differences from a regression of dummy variables of primary cooking fuel on the treatment dummy, controlling for household fixed effects and province-year dummies. The sample size is 20,140. The standard error is clustered by district.

The program effect on nondurable expenditures. Table 4.7 shows the estimated program effect on the propensity to spend on subcategories of monthly expenditure. The dependent variables are all log transformed percapita monthly expenditure. Each Dependant variable is indicated on each column. The utility bills in column 3 includes fuel, electricity, water and telephone. Transportation column 4 includes bus fare, cab fare, vehicle repair costs, fuel and the like. Rotating savings club in column 5 is known as *arisan*. Household items in column 6 includes laundry soap, cleaning supplies, anti-mosquitoes and the like. Personal toiletries in column 7 includes soap, shaving supplies, cosmetics and the like. Sweepstakes in column 9 includes lotteries, and the like. Total monthly expenditure in column 10 is the aggregate monthly expenditure which is the sum of column 1-9. All regressions use households and month-year fixed effects. The mean dependent variable is percapita monthly expenditure in USD.

The program reduces households' utility bills by 70%, or about 6 USD per month. By switching to LPG, households also reduce their cleaning expenses up to 70% (in column 6 and 7), or about 2 USD per month in total. With cleaner fuel like LPG, it is possible that the kitchen would be cleaner and the households members who do the cooking do not need to clean the kitchen or themselves as often as when they use kerosene. The transportation expenditure is decrease, likely because in some cases, kerosene can be mixed with gasoline used in transportation. Since kerosene is limited, this reduction could reflect the reduction in kerosene usage. I do not see any effect on any other subcategories of monthly expenditures.

Table 4.8 shows the estimated program effect on the propensity to spend on categories of yearly expenditure as well as weekly working hours. The dependent variables for column 11-15 are log transformed percapita yearly expenditure and for column 16 is percapita working hours per week. All regressions use households and month-year fixed effects. The mean dependent variable is percapita expenditure in USD or working hours per week.

Where does the reduction in the expenditures is spent on? I do not see any increase in other expenditure categories which might indicate that since the 'savings' are small compared to the total expenditure, households might distribute this small savings equally to other expenditures without noticing it. To some extend, these results support the consumption smoothing hypothesis.

Table 4.7: The propensity to spend on subcategories of monthly expenditures

	(1) Strictly non-durables	(2) Food	(3) Utility bills	(4) Transportation	(5) Rotating savings
ProgramX2014	-0.535	0.017	-0.704***	-0.687**	0.403
Standard error	(0.505)	(0.089)	(0.187)	(0.344)	(0.556)
Obs.	19,935	20,051	20,051	20,051	20,051
R-squared	0.418	0.539	0.490	0.450	0.542
Mean dep. var.	5.06	31.28	8.75	5.9	2.41

	(6) Household expenses	(7) Personal toiletries	(8) Servants' wages	(9) Sweeptakes	(10) Total exp.
ProgramX2014	-0.497***	-0.692***	0.480	0.009	-0.071
Standard error	(0.161)	(0.202)	(0.310)	(0.053)	(0.099)
Obs.	20,051	20,051	20,051	20,051	19,886
R-squared	0.319	0.367	0.446	0.276	0.628
Mean dep. var.	1.49	1.87	0.91	0.41	74.77

Notes: The dependent variables are all log transformed percapita monthly expenditure. Each Dependant variable is indicated on each column. The utility bills in column 3 includes fuel, electricity, water and telephone. Transportation column 4 includes bus fare, cab fare, vehicle repair costs, fuel and the like. Rotating savings club in column 5 is known as *arisan*. Household items in column 6 includes laundry soap, cleaning supplies, anti-mosquitoes and the like. Personal toiletries in column 7 includes soap, shaving supplies, cosmetics and the like. Sweepstakes in column 9 includes lotteries, and the like. Total monthly expenditure in column 10 is the aggregate monthly expenditure which is the sum of column 1-9. All regressions use households and month-year fixed effects. The mean dependent variable is percapita monthly expenditure in USD. 1 USD = Rp 13,000.

Effect of the program on each component in utility bills. Table 4.9 reports the estimate of each component of the utility bills. The dependent variables used in each column are log percapita monthly expenditure on fuel (column 1-2), electricity (column 3-4), water (column 5-6) and telephone (column 7-8). Model 1, 3, 5, and 7 capture the regression coefficient within district, while model 2, 4, 6, and 8 capture within household, controlling for the interview month. Note that the sample uses only IFLS 2007 and 2014, since only the last two surveys break down the utility bill components.

Table 4.8: The propensity to spend on categories of yearly expenditures and weekly working hours

	(11)	(12)	(13)	(14)	(15)	(16)
			Yearly expenditure			Per week
	Education	Charity	Medical	Durables	Last year income	Working hours
ProgramX2014	-0.535	-0.133	-0.493	0.115	-0.837	3.671
Standard error	(0.505)	(0.278)	(0.600)	(0.403)	(0.633)	(2.429)
Obs.	19,935	20,051	20,051	20,051	20,094	20,094
R-squared	0.418	0.371	0.378	0.454	0.439	0.486
Mean dep. var.	5.06	29.19	16.3	80.21	301.65	23.42

The dependent variables for column 11-15 are log transformed percapita yearly expenditure and for column 16 is percapita working hours per week. All regressions use households and month-year fixed effects. The mean dependent variable is percapita expenditure in USD or working hours per week. 1 USD = Rp 13,000.

Fuel expense is the main share in the utility bill, and it is the main driver of the reduction in households' utility bills. The fuel expense declines by about 40%, about the same magnitude as the declines in the total utility bills. There are some reduction in the electricity expense as well, which could indicates that households might shift from cooking with electricity, to cooking with LPG. Water expense is increase, but the sample size is significantly smaller due to missing data.

The estimates shows that the program reduces household fuel expenses by 1.19 USD. The magnitude of the effect is within the same range as several surveys conducted within small sample size, up to 1.64 USD (Andadari et al., 2014; Budya and Arofat, 2011). The electricity expense is increase about 13%, although not statistically significant, in contrast with Andadari et al. (2014) findings that the conversion program led to an increasing consumption of both electricity and traditional biomass as households are stacking fuels.

4.4.2 Timing of the program

Here, I explore if the results are differ by the duration of the program. I classified households who are treated in 2007-2010 as early treated group and households who are treated in 2011-2013 as late treated group. Panel A in Table 4.10 shows

Table 4.9: Effect of the program on each component in utility bills

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Fuel exp.		Electricity exp.		Water exp.		Telephone exp.	
ProgamX2014	-0.455***	-0.439**	-0.154*	-0.134	0.013	0.248*	0.101	0.054
	(0.136)	(0.182)	(0.087)	(0.145)	(0.074)	(0.146)	(0.076)	(0.147)
Obs.	8,443	8,443	9,104	9,104	2,835	2,835	6,660	6,660
R^2 stat	0.133	0.682	0.238	0.802	0.377	0.895	0.176	0.776
District FE	Y		Y		Y		Y	
Household FE		Y		Y		Y		Y
Mean dep. var.	2.71		5.77		1.73		16.96	
Month FE		Y		Y		Y		Y

Each column reports the estimated differences from a regression of log percapita monthly expenditure on fuel (column 1-2), electricity (column 3-4), water (column 5-6) and telephone (column 7-8) on the treatment dummy. Model 1, 3, 5, and 7 capture the regression coefficient within district, while model 2, 4, 6, and 8 capture within household, controlling for the interview month. The standard error is clustered by district. The sample uses only IFLS 2007 and 2014 which are the only two survey that breakdown the utility bills component.

the pre-implementation period, and Panel B shows the program effect based on the alternative treatment and control groups.

Table 4.10 shows coefficient estimates β_3 from Eq. 4.1 with different sets of treatment and control group. As the treatment group, column 1-2 and 5-6 use early treated households, and column 3-4 use late treated households. As the control group, column 1-4 use untreated households, and column 5-6 use late treated households. Panel A uses sample prior to the program to show pre-implementation trend between treatment and control groups. Panel B uses full sample to look at the program effect on the log utility bills.

The program effect on the utility bills for early treated households are very similar with earlier estimation in Table 4.7 column 3. On the other hand, the reduction in the utility bills for late treated households are only about half of the earlier result, 26%. This is as expected considering that the program is implemented gradually. Table 4.10 in Appendix confirm that the reduction in kerosene purchased is less precise when I compare late treated group as the control and untreated groups as the control.

Table 4.10: Effect of the program with alternative control groups on utility bills

	(1)	(2)	(3)	(4)	(5)	(6)
	Early vs Untreated		Late vs Untreated		Early vs Late Treated	
Panel A. Before the program						
ProgramX2007	-0.034	0.010	0.008	0.089	-0.044	-0.034
Standard Error	(0.091)	(0.115)	(0.117)	(0.176)	(0.080)	(0.098)
Obs.	8,589	8,589	1,884	1,884	9,594	9,594
R^2 stat	0.381	0.800	0.396	0.833	0.374	0.798
Panel B. Full sample						
ProgamX2014	-0.388***	-0.409***	-0.328***	-0.264**	-0.057	-0.061
Standard Error	(0.094)	(0.115)	(0.106)	(0.126)	(0.053)	(0.063)
Obs.	12,654	12,654	2,794	2,794	14,135	14,135
R^2 stat	0.384	0.739	0.395	0.758	0.377	0.736
District FE	Y		Y		Y	
Household FE		Y		Y		Y
Month FE		Y		Y		Y

As the treatment group, column 1-2 and 5-6 use early treated households, and column 3-4 use late treated households. As the control group, column 1-4 use untreated households, and column 5-6 use late treated households. Panel A uses sample prior to the program to show pre-implementation trend between treatment and control groups. Panel B uses full sample to look at the program effect on the log utility bills (β_3 coefficient from Eq. 4.1). The standard error is cluster by district.

4.4.3 Differences in responses across households

Following the literature, for each variable, I split households into three groups by percapita household yearly expenditure: below 33th percentile, below 66th percentile and above 66th percentile. Table 4.11 shows the estimated differences on each subcategories of expenditure by the groups with income below 33th percentile (column 1-4) and income above 66th percentile (column 5-8), controlling for household fixed effects and month-year interview date dummies. The outcome variables are a log transformation of percapita monthly expenditure stated in each column.

The effect of the program is larger for 'poor' households, although there is a large standard error for the effect of the program on the utility bills. In total the reduction in the expenditure is larger for 'richer' households. For the transportation expenditure, there are no significant effect on both groups.

Table 4.11: Effect of the program across different households

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Below 33th percentile				Above 66th percentile			
	Utility bills	Household expens-es	Personal toi-letries	Trans-portation	Utility bills	Household expens-es	Personal toi-letries	Trans-portation
ProgamX2014	-0.868	-0.612	-0.881**	0.263	-0.635**	-0.387	-0.400	-0.168
	(0.625)	(0.406)	(0.341)	(0.911)	(0.289)	(0.587)	(0.415)	(0.539)
Standard error								
Observations	6,629	6,629	6,629	6,629	6,628	6,628	6,628	6,628
R-squared	0.571	0.536	0.551	0.584	0.673	0.503	0.542	0.607
Mean dep. var.	1.11	.34	.34	.54	22.76	3.53	4.64	15.41

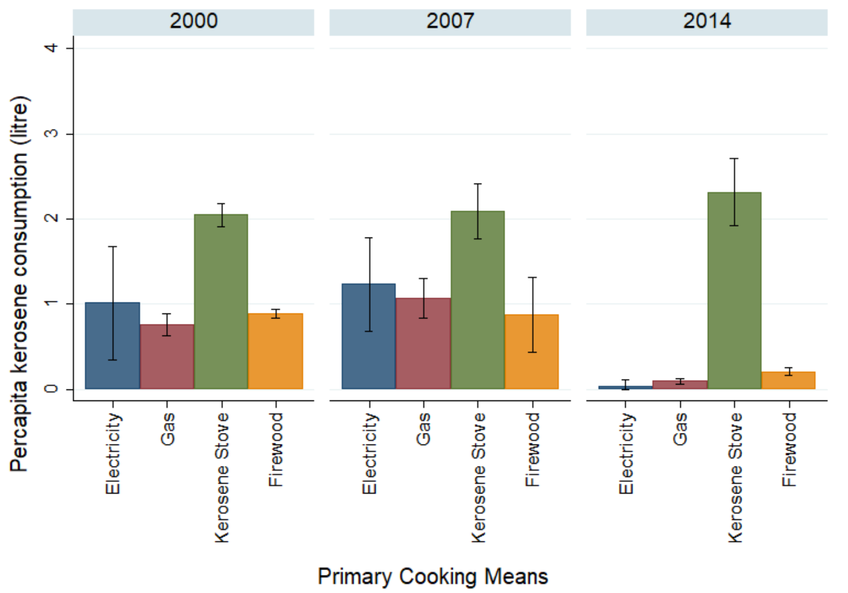
Notes: Each column reports the estimated differences on each subcategories of expenditure by the groups with income below 33th percentile (column 1-4) and income above 66th percentile (column 5-8), controlling for household fixed effects and month-year interview date dummies. The outcome variables are a log transformation of percapita expenditure stated in each column. The standard error is clustered by district.

4.5 Robustness

4.5.1 Fuel stacking

Fuel stacking is common. In general, households tend to stack fuels rather than moving away from previously used fuels when adopting a new fuel (Jeuland et al., 2015). Figure 4.2 is consistent with this argument. Before the program, households who use kerosene as their main cooking means, on average, bought about two litre of kerosene. Other households, who use other cooking means, bought about one litre of kerosene, on overage. This fuel mix is often unrecorded in the national survey data and using dummies for primary cooking fuel does not capture the actual fuel consumption very well. But IFLS includes measures on quantity and prices for kerosene purchase starting from the year 2000. Thus, in the next section, I discuss the impact on kerosene quantity and kerosene price.

Figure 4.2: Percapita of kerosene consumption by primary cooking fuel

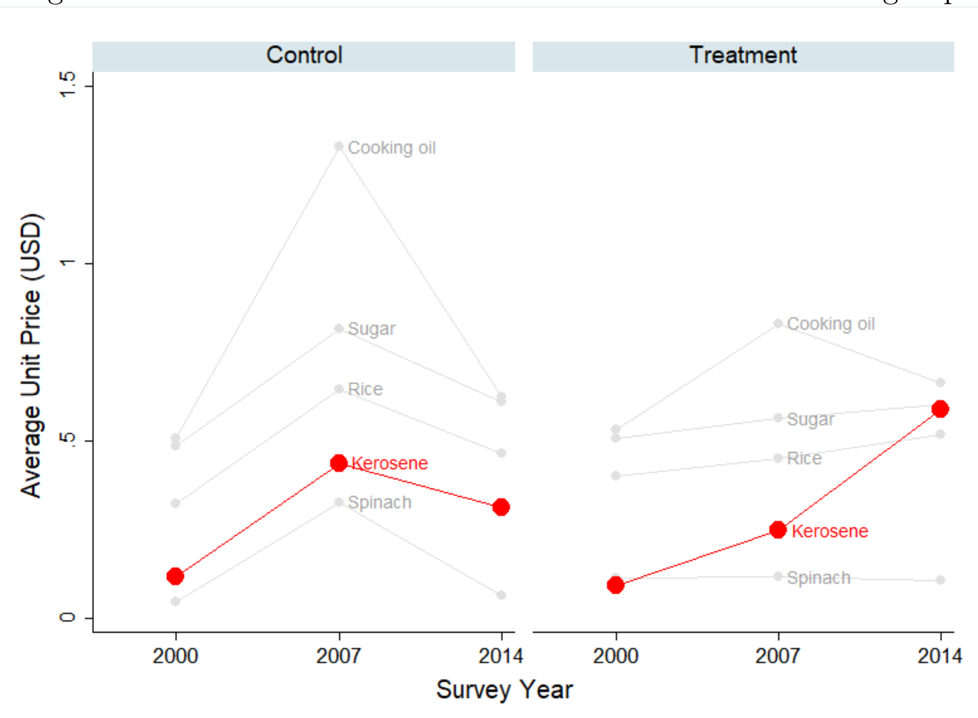


This figure plots the average percapita of kerosene consumption from the recent purchase by households' primary cooking fuel.

4.5.2 Falsification

Some concurrent changes might happen within the same time as this program. A clear example would be 2007-2008 global financial crisis. The concern is that the effect of the crisis contaminate the effect of the policy. The program will impact only kerosene and LPG, in contrast to crisis which impact all commodities. Figure 4.3 shows that on the financial crisis year, prices for most of the commodities is increased in both treatment and control districts. But in 2014 and only in the treatment group, kerosene price doubled. While in the control groups, kerosene price follows the same trend with other commodities. The graphical evidence provides some support that the program of the program on kerosene is unique and distinct from the persistent effect of the crisis.

Figure 4.3: Trend of Kerosene Price in Treatment and Control group



This figure plots the average of CPI adjusted kerosene price per litre and other main household's food commodities. 1 USD = Rp 13,000.

4.6 Discussion

This paper investigates on the extent to which the switching improves households well-being. Burning dirty cooking fuels produces harmful air pollutants and has long been associated with poor health and low productivity. The desirability to switch to a cleaner fuel depends critically on the extent to which the switching improves households well-being. Using a nationwide transition from kerosene to cleaner burning propane in Indonesia, I investigate households consumption response to fuel switching. Based on combustion efficiency and end-use energy equivalence, LPG is cleaner and more efficient than kerosene. Using variation in the timing of the implementation on four waves of the Indonesia longitudinal survey, I compare changes in expenditure within households in the treated districts with changes in expenditure within households in not-yet treated districts. I find that households reduce their kerosene consumption up to 100% and their fuel expenses are reduced by 40%, or 1.19 USD per month on average. These effects are higher among poor households. I do not find any response to other nondurable expenditures which provides some evidence of consumption smoothing. This is as expected considering the size of the effect is only about a 2% reduction from total monthly expenditure. As fuel demand is inelastic, a small cost saving might indicate big welfare improvement. Adding to the literature of the benefit of switching to a cleaner fuel, the overall impact of this on-going fuel switching intervention can be enormous.

Appendix A

Appendix to Chapter 2

Comparison between included and excluded group

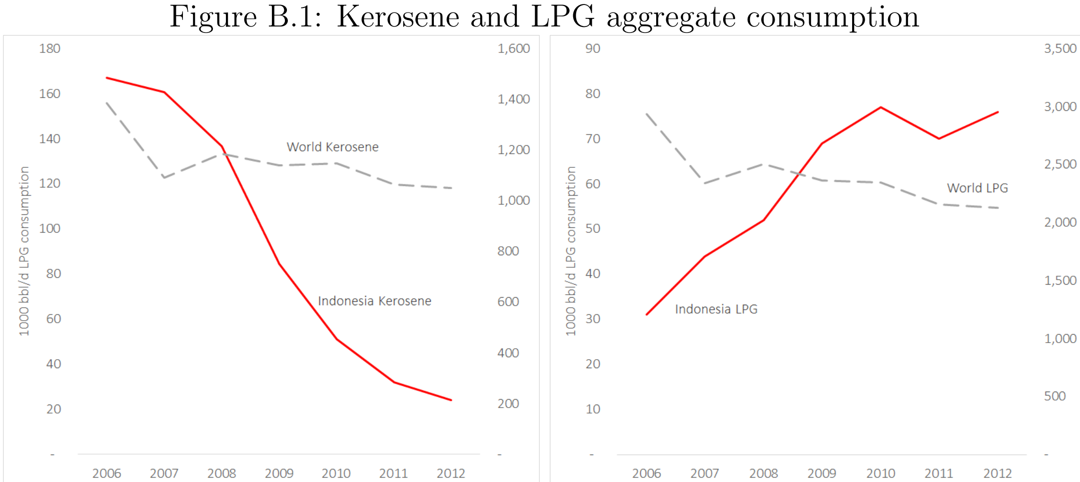
Table A.2 shows the mean difference between control group (untreated districts by 2011), treatment group included in the analysis (treated districts in 2009-2011) and treatment group excluded in the analysis (treated in 2007-2008) at baseline. Excluded regions are more developed regions thus have significantly better health facilities, infrastructure such: road, electricity, sanitation, access to clean water, and school, and significantly have more income and labor force participation. They are also densely populated with 89 districts in the group that account for almost half of the country's population. Using treatment groups in column 2 does improve comparability between treatment and control groups.

Similar to Table 2.2 that compares baseline household characteristics between treated and control group but Table A.2 compares households within the treatment group (i.e. excluded group compares to the included group). also compares shows looks more similar to the control group although there are some characteristics that are different, the magnitude are small. The main analysis will focus on districts in column 1 and 2 which accounts for 80% of the total districts and 50% of the total population.

Characteristics of the compliers

To understand more about the characteristics of the compliers, I plot the density of fuel choice based on wealth index before and after the program. Figure A indicates a high program compliance: the compliers are likely household who use kerosene before the program which is the target of the program. Wealth index is a variable that summarize household dwelling characteristics and asset ownership using principal component analysis. It ranges from -2.75 to 3.17 in the sample, where the more negative indicates the poorer households and the more positive indicates the richer households. LPG users was dominated by richer and richest households before the program, but it shifts to middle and richer household after the program. Kerosene users loose a portion of richer household who seems to switch to LPG. The figure shows that the characteristics of wood users seems to be similar across time.

Figure B.1: Kerosene and LPG aggregate consumption



Notes: Primary y-axis corresponds to Indonesia's consumption, while secondary y-axis corresponds to world's consumption. In 2006, Indonesia consumes 10% of world kerosene consumption and 1% of world LPG consumption. In 2012, Indonesia's kerosene consumption decreases to 2.3% and Indonesia's LPG consumption increases to 3.5% of the world's total consumption. These large variation only happened in Indonesia. Kerosene consumption excludes jet fuel. Source: U.S. Energy Information Administration.

Table A.1: Differences in district characteristics at baseline

District characteristics	Mean: Control group (1)		Mean: Treatment group, Included (2)		Mean: Treatment group, Excluded (3)		Mean Difference: Included (1)-(2)		Mean Difference: Excluded (1)-(3)	
Health characteristics										
Number of doctors	29.1	(2.57)	74.25	(8.83)	225.4	(28.59)	45.15***	(9.20)	196.30***	(28.74)
Number of hospitals	2.36	(0.19)	4.11	(0.46)	7.64	(0.74)	1.75***	(0.50)	5.29***	(0.77)
Number of midwives	133.87	(5.84)	230.62	(13.08)	332.58	(19.49)	96.74***	(14.33)	198.71***	(20.37)
Number of village polyclinic	49.56	(2.99)	84.66	(6.76)	100.41	(8.91)	0.04***	(0.01)	0.05***	(0.01)
Number of community health centre (puskesmas)	60.43	(2.66)	79.44	(3.3)	94.04	(5.25)	0.02***	(0.00)	0.03***	(0.01)
Infrastructure characteristics										
Villages with asphalt road (in % of total villages)	50.11	(2.04)	64.74	(1.98)	78.86	(2.12)	14.63***	(2.85)	28.75***	(2.95)
Access to electricity (in % of total household)	68.57	(1.71)	85.19	(1.11)	97.27	(0.54)	16.62***	(2.04)	28.70***	(1.79)
Access to safe sanitation (in % of total Household)	51.93	(1.29)	60.82	(1.39)	64.42	(1.41)	8.89***	(1.89)	12.49***	(1.92)
Access to safe water (in % of total household)	40.47	(1.25)	45.17	(1.48)	56.94	(1.76)	4.70**	(1.94)	16.47***	(2.16)
Number of schools at primary level	174.89	(7.96)	370.71	(21.33)	680.38	(43.69)	0.20***	(0.02)	0.51***	(0.04)
Economic Indicators										
Household per capita expenditure (in '000 IDR)	228.53	(5.5)	230.5	(5.29)	267.27	(11.74)	1.97	(7.64)	38.74***	(12.98)
Literacy rate age¿15 (in % of total population)	91.02	(0.75)	90.6	(0.63)	91.66	(0.62)	-0.00	(0.00)	0.00	(0.00)
Monthly per capita education expenditure (in '000 IDR)	6.98	(0.34)	8.97	(0.41)	16.15	(1.2)	1.99***	(0.54)	9.17***	(1.25)
Monthly per capita health expenditure (in '000 IDR)	3.95	(0.15)	4.67	(0.15)	6.66	(0.3)	0.72***	(0.21)	2.72***	(0.33)
Population										
Number of people employed (in '000 people)	83.58	(4.39)	224.82	(14.38)	534.58	(32.69)	141.24***	(15.05)	451.01***	(33.04)
Number of people in labor force (in '000 people)	89.59	(4.75)	243.47	(15.55)	599.15	(37.85)	153.88***	(16.27)	509.55***	(38.21)
Number of people below the poverty line (in '000 people)	40.79	(2.58)	93.84	(7.37)	169.79	(12.54)	53.05***	(7.82)	129.00***	(12.82)
Total population (in '000 people)	61.62	(3.34)	168.43	(10.57)	382.72	(27.93)	106.81***	(11.10)	321.10***	(28.17)
Fraction of the population (2005)	15%		36%		49%					
Number of districts	184		163		89					

Notes: The control group represent untreated districts. The treatment group represents treated districts in 2009-2011 (included) and 2007-2008 (excluded). Each entry in the mean difference column reports coefficient of the difference from treated and untreated group (=1 if the district is treated) from a separate regression when using the respective variable as the dependent variable. Standard errors (in parentheses) are clustered by district. 1 USD ≈ 9,379 IDR in 2007. Source: INDO DAPOER
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A.2: Baseline characteristics between included and excluded group in the treated districts

	Mean of treated districts				Within-district			
	Included group		Excluded group		Level differences		Trend differences	
	(1)		(2)		(3)		(4)	
Total observations	14,667		8,097					
Cooking fuel choice								
LPG	0.09	(0.01)	0.21	(0.02)	-0.06***	(0.02)	0.01	(0.02)
Kerosene	0.40	(0.02)	0.48	(0.03)	0.07***	(0.02)	0.01	(0.02)
Wood	0.50	(0.03)	0.30	(0.04)	-0.05***	(0.02)	-0.03	(0.02)
Birth outcomes								
Infant death	0.04	(0.00)	0.03	(0.00)	-0.02***	(0.00)	-0.00	(0.01)
Perinatal death	0.02	(0.00)	0.01	(0.00)	-0.04***	(0.00)	0.00	(0.00)
Low weight (<2500 g)	0.13	(0.01)	0.12	(0.00)	0.05***	(0.01)	-0.01	(0.01)
Birth weight (in kilogram)	3.20	(0.01)	3.15	(0.01)	-0.07***	(0.01)	0.02	(0.02)
Birth characteristics								
Antenatal visits	6.31	(0.12)	8.40	(0.30)	-0.56***	(0.13)	0.29*	(0.18)
Age at birth	27.35	(0.09)	27.67	(0.09)	-2.31***	(0.18)	0.41*	(0.24)
Mother's age <19	0.06	(0.00)	0.04	(0.00)	0.07***	(0.01)	-0.02**	(0.01)
First birth	0.33	(0.01)	0.38	(0.01)	0.03***	(0.01)	-0.02	(0.01)
Child born in the last 5 years	1.37	(0.01)	1.26	(0.01)	-0.05***	(0.01)	0.03**	(0.01)
Household characteristics								
Number of household member	5.43	(0.04)	5.48	(0.07)	-1.00***	(0.07)	0.12	(0.09)
Has TV	0.61	(0.02)	0.81	(0.02)	0.12***	(0.01)	-0.01	(0.02)
Has fridge	0.21	(0.01)	0.35	(0.03)	-0.13***	(0.02)	0.03	(0.02)
Has clean water for drinking	0.25	(0.02)	0.38	(0.03)	-0.23***	(0.03)	0.12***	(0.03)
Visited health facility last 12 months	0.46	(0.01)	0.53	(0.02)	-0.10***	(0.03)	-0.01	(0.04)
Do not smoke	0.99	(0.00)	0.98	(0.00)	0.02***	(0.00)	-0.01	(0.01)
Do not have own toilet	0.60	(0.02)	0.42	(0.03)	0.16***	(0.02)	0.03	(0.03)
Has electricity	0.83	(0.02)	0.96	(0.01)	-0.02**	(0.01)	-0.04*	(0.02)
Parents' education								
Mother: secondary and higher	0.53	(0.02)	0.59	(0.03)	-0.03*	(0.02)	0.02	(0.02)
Spouse: secondary and higher	0.57	(0.02)	0.63	(0.03)	-0.11***	(0.02)	0.04*	(0.02)

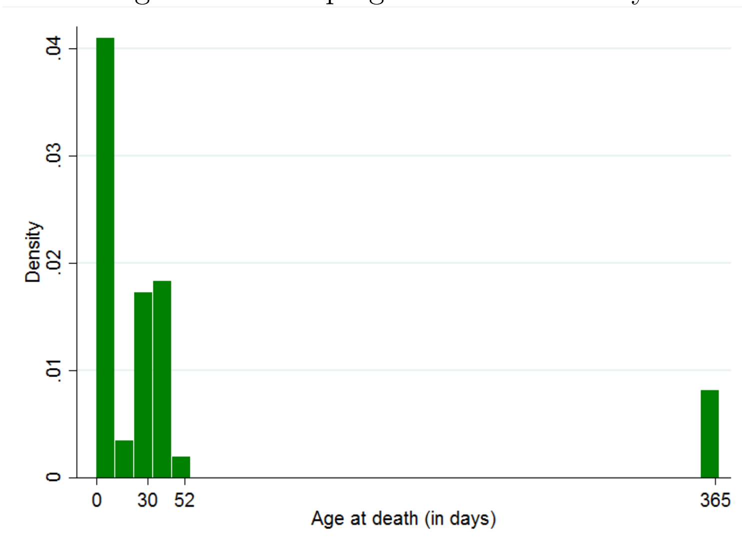
Notes: The table compares within district differences between treated groups. Column 1 reports average characteristics for household in districts included in the main analysis. Column 2 reports average characteristics of household in the districts excluded in the main analysis. Column 3 reports the within-district mean differences between households in column 1 and 2. Column 4 reports within-district trend. All regressions include district fixed effects. Standard errors in parentheses are clustered at the district level.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A.3: Policy effect on infant mortality, perinatal mortality and acute respiratory infection

	Infant mortality		Perinatal Mortality		ARI[b]	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.010**	-0.012***	-0.007**	-0.008**	-0.002	-0.007
	(0.004)	(0.004)	(0.003)	(0.004)	(0.024)	(0.027)
Has TV	0.003	0.004	0.002	0.002	-0.008	-0.007
	(0.003)	(0.003)	(0.002)	(0.002)	(0.012)	(0.012)
Has fridge	-0.004	-0.004	-0.002	-0.002	-0.035***	-0.035***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.013)	(0.013)
Has clean water for drinking	-0.005**	-0.005*	-0.003	-0.002	-0.019	-0.019
	(0.002)	(0.002)	(0.002)	(0.002)	(0.012)	(0.013)
Visited health facility last 12 months	-0.007***	-0.007***	-0.004**	-0.004**	0.007	0.008
	(0.002)	(0.002)	(0.002)	(0.002)	(0.010)	(0.010)
Do not smoke	-0.025**	-0.025**	-0.010	-0.010	-0.070**	-0.072**
	(0.011)	(0.011)	(0.008)	(0.008)	(0.034)	(0.035)
Do not have own toilet	0.002	0.001	0.000	0.000	0.028**	0.028**
	(0.003)	(0.003)	(0.002)	(0.002)	(0.011)	(0.011)
Has electricity	-0.008*	-0.007*	0.001	0.001	-0.015	-0.014
	(0.004)	(0.004)	(0.003)	(0.003)	(0.016)	(0.016)
Mother: secondary and higher	-0.009***	-0.009***	-0.004*	-0.004*	-0.007	-0.007
	(0.003)	(0.003)	(0.002)	(0.002)	(0.012)	(0.012)
Spouse: secondary and higher	-0.001	-0.001	0.003	0.003	-0.004	-0.005
	(0.002)	(0.002)	(0.002)	(0.002)	(0.011)	(0.011)
Mother: no education	0.002	0.002	-0.006	-0.006	-0.003	-0.004
	(0.007)	(0.007)	(0.004)	(0.004)	(0.029)	(0.028)
Spouse: no education	0.013	0.013	0.003	0.003	-0.040	-0.044
	(0.008)	(0.008)	(0.005)	(0.005)	(0.034)	(0.035)
Age at birth	0.000	0.000	0.000	0.000	-0.003**	-0.002**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Mother's age <19	0.018***	0.018***	0.014***	0.014***	0.010	0.015
	(0.006)	(0.006)	(0.005)	(0.004)	(0.022)	(0.022)
First birth	-0.168	-0.160	0.012***	0.010	-0.120	-0.067
	(0.174)	(0.171)	(0.004)	(0.009)	(0.402)	(0.376)
Constant	0.199	0.150	-0.034***	-0.027**	0.586	0.358
	(0.179)	(0.173)	(0.012)	(0.013)	(0.434)	(0.410)
Observations	38,888	38,888	38,890	38,890	12,192	12,192
R-squared	0.049	0.055	0.035	0.041	0.065	0.080
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month-year FE	No	Yes	No	Yes	No	Yes

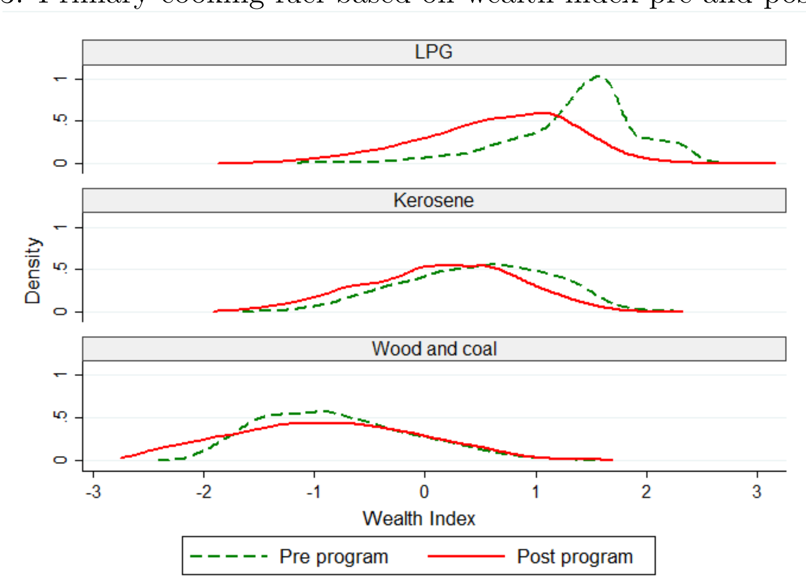
Notes: The table shows the coefficient of some control variables in the main DID regression (complete version of Table 2.5). All regressions are using the base regression with the set of control variables mentioned in Section 2.3.1. The column (1) and (2) use infant mortality as the outcome variables, column (3) and (4) use perinatal mortality and column (5) and (6) use ARI (i.e. acute respiratory infection is a self reported health symptom indicated by cough and followed by short rapid breath and broadly known as an indication of pneumonia) as the outcome variable. [b]ARI only recorded within two weeks preceeding the survey. Standard errors in parentheses are clustered at the district level.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Figure B.2: Heaping in infant mortality



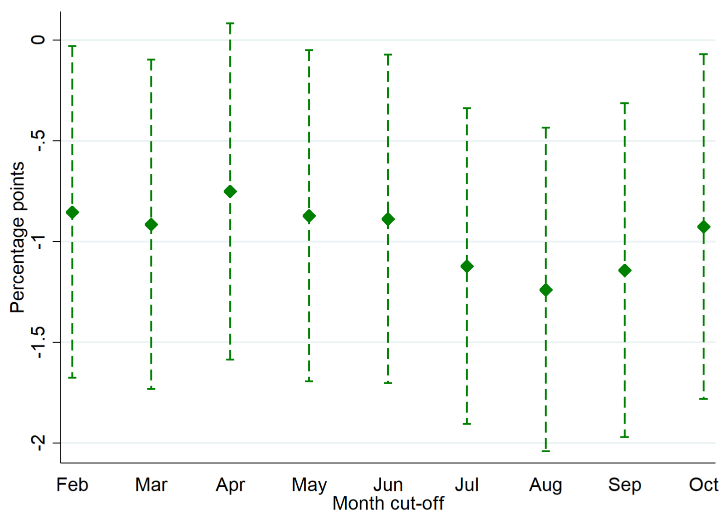
Notes: The density plot the age at death of infant in days. There is heaping near 0 and 30 days. Infant deaths within these range are included as infant mortality in the analysis.

Figure B.3: Primary cooking fuel based on wealth index pre and post program



Notes: The density plot shows fuel choice based on wealth index before and after the program. Pre program uses survey wave 2002 and 2007 while post program uses survey wave 2012. Wealth index variable is a constructed variable in the survey using principal component analysis on composite measure of a household's cumulative living standard such as dwelling characteristics and household assets. It ranges from -2.75 to 3.17 in the sample, where the more negative indicates the poorer households and the more positive indicates the richer households.

Figure B.4: Robustness with the cut off month



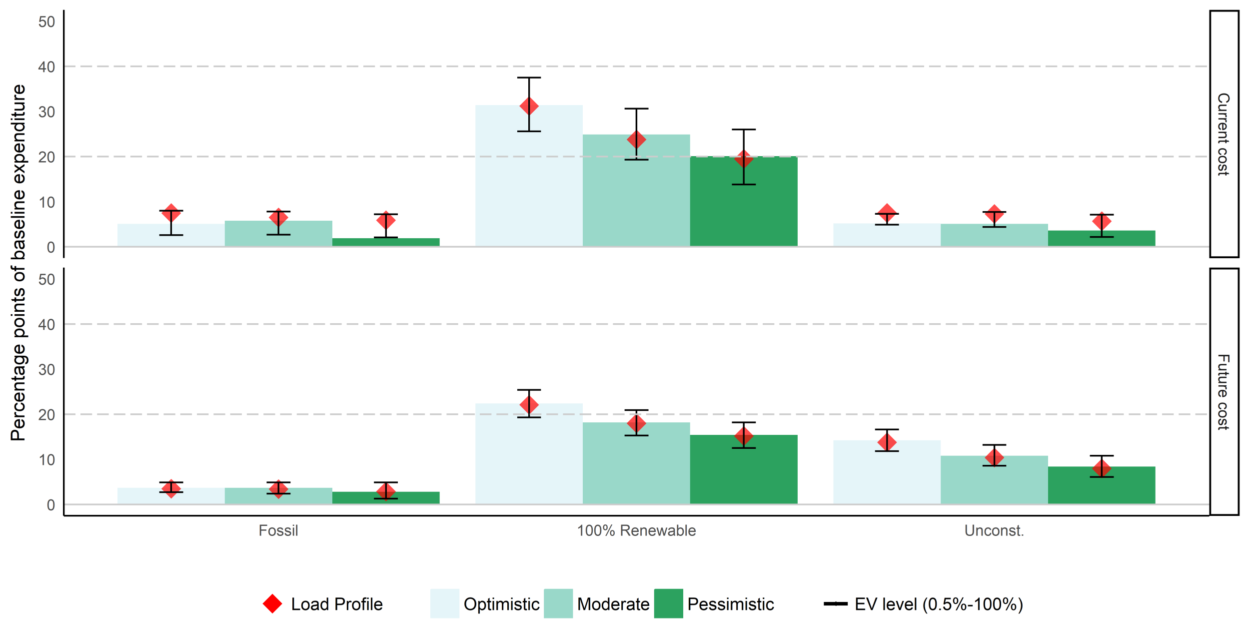
Notes: This figure plots each coefficient of the treatment effect from a separate regression using different monthly births cut-off indicated in y-axis. For example, for February cut-off, I match births occurred after February 2009 to districts that had the program implemented in 2009 as the treatment group.

Appendix B

Appendix to Chapter 3

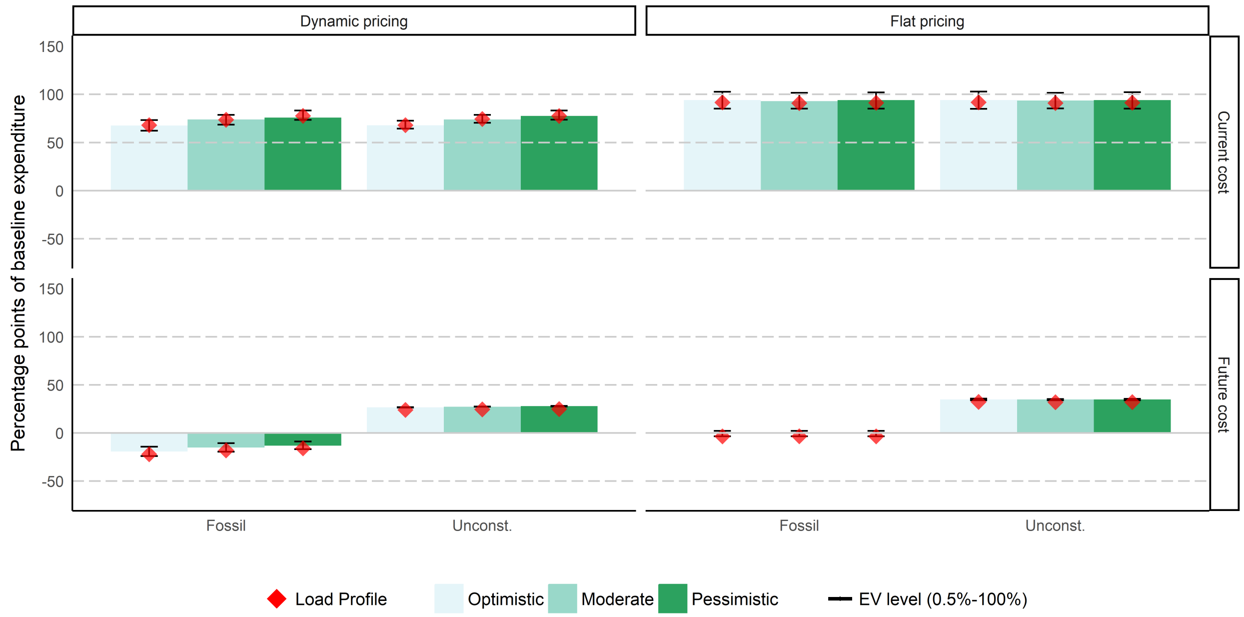
B.1 Supplementary Results

Figure B.1: Surplus gain from dynamic pricing under different policy, cost and demand flexibility scenarios when the overall demand elasticity equals 0.5.



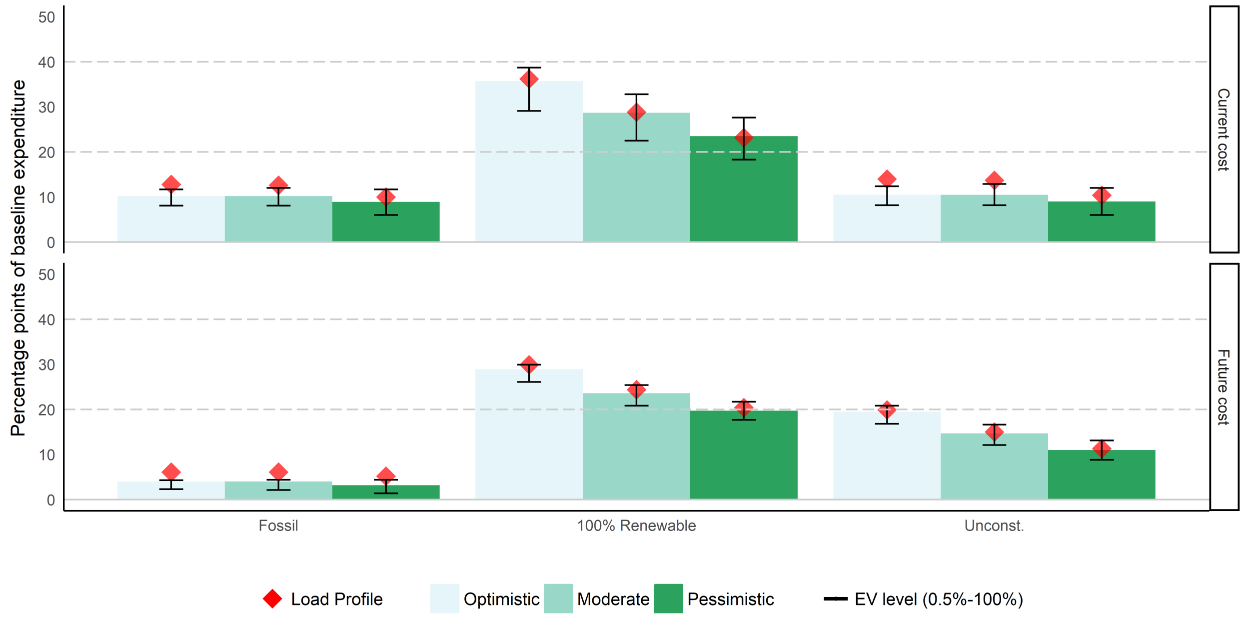
The graph shows the difference in total economic surplus with real-time marginal-cost pricing and total surplus when prices are flat, holding all else the same. Total surplus change is reported as a percentage of baseline (flat price) expenditure on electricity. The graph depicts all scenarios with an overall demand elasticity of 0.5 instead of 0.1 as reported in the main paper. The top row shows the value of variable pricing under current costs; the bottom row shows the value of variable pricing under projected future costs (2045). The horizontal axis shows the policy scenario: fossil, 100% renewable or unconstrained (maximum surplus, regardless of source). The bars show the baseline case with 50 percent electric vehicle fleet and 2045 load profile, the diamonds show the 2007 load profile, and the error bars show how results differ with 0.5 percent and 100 percent electric vehicles–more electric vehicles always increase the value of variable pricing.

Figure B.2: Cost of 100 percent renewable energy system under different policy, cost and demand flexibility scenarios when the overall demand elasticity equals 0.5.



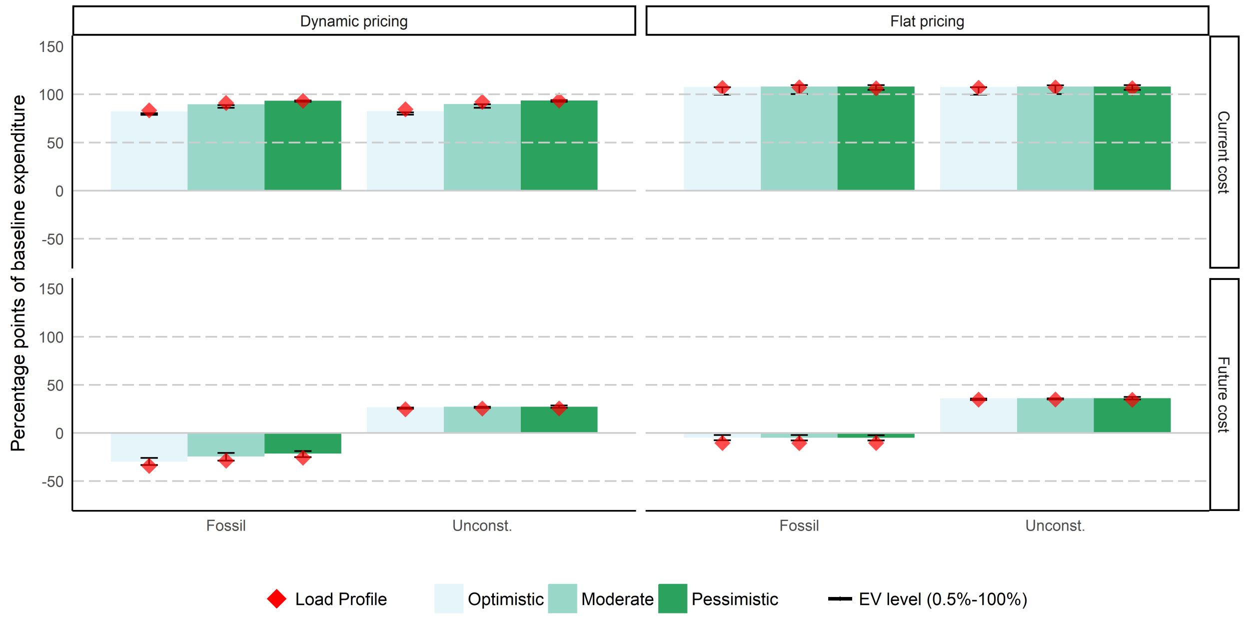
The graph shows the difference in total economic surplus with a 100 percent renewable system versus the baseline scenario given on the horizontal axis, holding all else the same. Total surplus change is reported as a percentage of baseline expenditure on electricity. The graph depicts all scenarios with an overall demand elasticity of 0.5 instead of 0.1 as reported in the main paper. The top row shows the value of variable pricing under current costs; the bottom row shows the value of variable pricing under projected future costs (2045). The horizontal axis shows the policy scenario: fossil, 100% renewable or unconstrained (maximum surplus, regardless of source). The bars show the baseline case with 50 percent electric vehicle fleet and 2045 load profile, the diamonds show the 2007 load profile, and the error bars show how results differ with 0.5 percent and 100 percent electric vehicles–more electric vehicles always increase the value of variable pricing.

Figure B.3: Surplus gain from dynamic pricing under different policy, cost and demand flexibility scenarios when the overall demand elasticity equals 0.9.



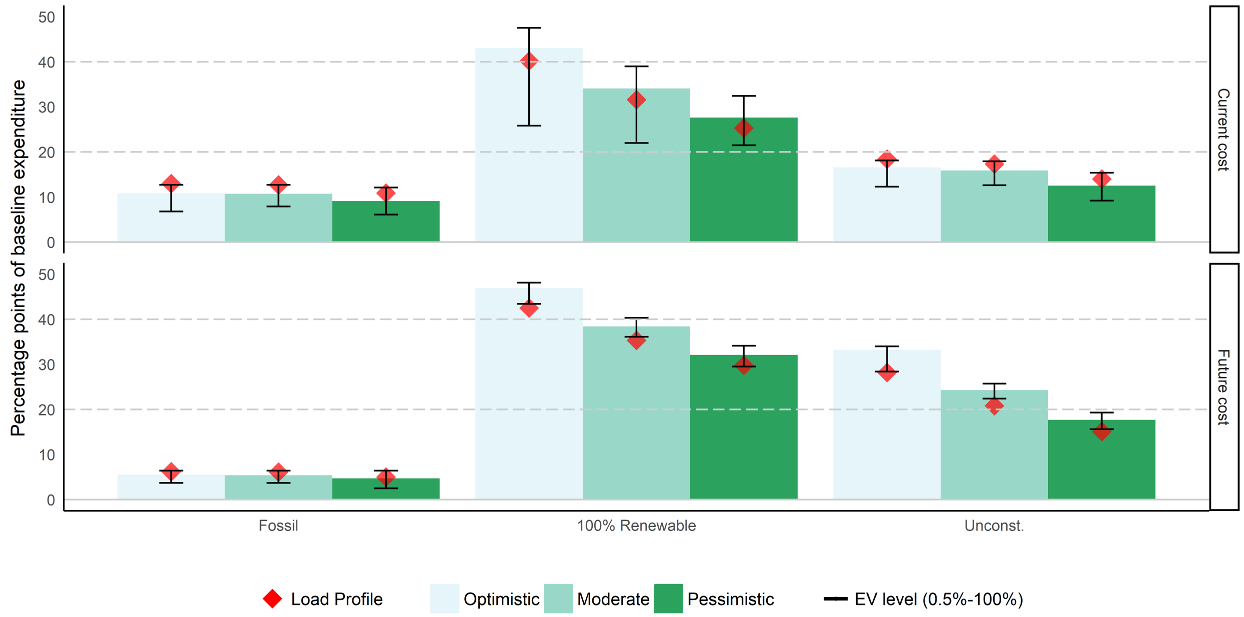
The graph shows the difference in total economic surplus with real-time marginal-cost pricing and total surplus when prices are flat, holding all else the same. Total surplus change is reported as a percentage of baseline (flat price) expenditure on electricity. The graph depicts all scenarios with an overall demand elasticity of 0.9 instead of 0.1 as reported in the main paper. The top row shows the value of variable pricing under current costs; the bottom row shows the value of variable pricing under projected future costs (2045). The horizontal axis shows the policy scenario: fossil, 100% renewable or unconstrained (maximum surplus, regardless of source). The bars show the baseline case with 50 percent electric vehicle fleet and 2045 load profile, the diamonds show the 2007 load profile, and the error bars show how results differ with 0.5 percent and 100 percent electric vehicles–more electric vehicles always increase the value of variable pricing.

Figure B.4: Cost of 100 percent renewable energy system under different policy, cost and demand flexibility scenarios when the overall demand elasticity equals 0.9.



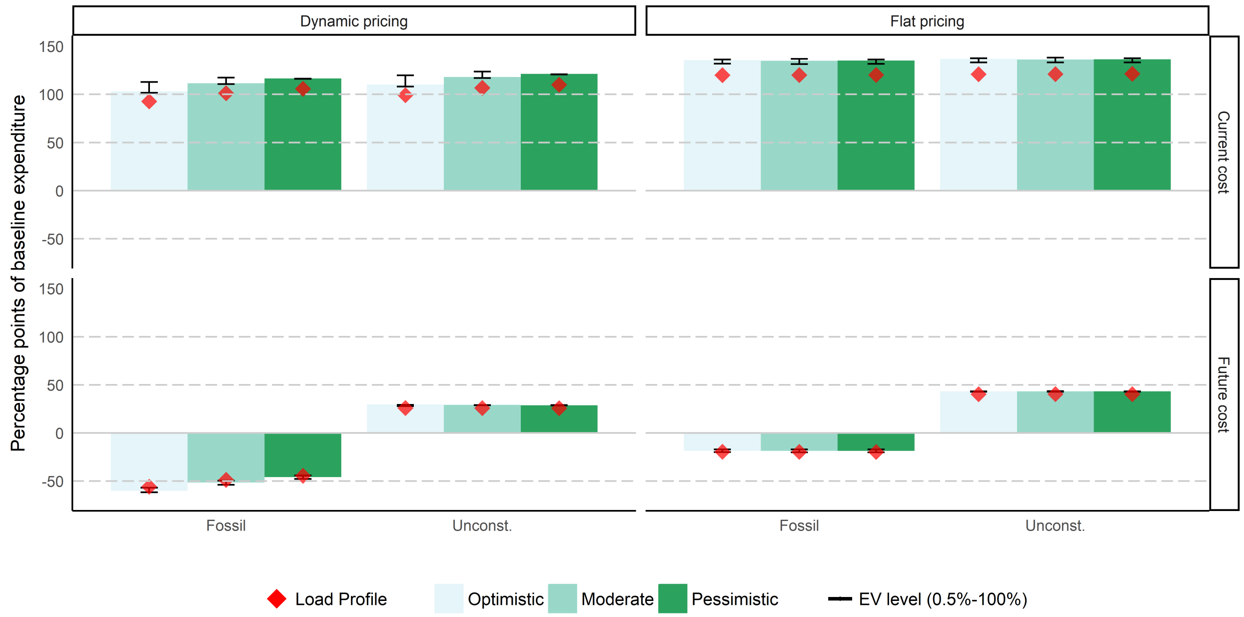
The graph shows the difference in total economic surplus with a 100 percent renewable system versus the baseline scenario given on the horizontal axis, holding all else the same. Total surplus change is reported as a percentage of baseline expenditure on electricity. The graph depicts all scenarios with an overall demand elasticity of 0.9 instead of 0.1 as reported in the main paper. The top row shows the value of variable pricing under current costs; the bottom row shows the value of variable pricing under projected future costs (2045). The horizontal axis shows the policy scenario: fossil, 100% renewable or unconstrained (maximum surplus, regardless of source). The bars show the baseline case with 50 percent electric vehicle fleet and 2045 load profile, the diamonds show the 2007 load profile, and the error bars show how results differ with 0.5 percent and 100 percent electric vehicles–more electric vehicles always increase the value of variable pricing.

Figure B.5: Surplus gain from dynamic pricing under different policy, cost and demand flexibility scenarios when the overall demand elasticity equals 2.



The graph shows the difference in total economic surplus with real-time marginal-cost pricing and total surplus when prices are flat, holding all else the same. Total surplus change is reported as a percentage of baseline (flat price) expenditure on electricity. The graph depicts all scenarios with an overall demand elasticity of 2 instead of 0.1 as reported in the main paper. The top row shows the value of variable pricing under current costs; the bottom row shows the value of variable pricing under projected future costs (2045). The horizontal axis shows the policy scenario: fossil, 100% renewable or unconstrained (maximum surplus, regardless of source). The bars show the baseline case with 50 percent electric vehicle fleet and 2045 load profile, the diamonds show the 2007 load profile, and the error bars show how results differ with 0.5 percent and 100 percent electric vehicles–more electric vehicles always increase the value of variable pricing.

Figure B.6: Cost of 100 percent renewable energy system under different policy, cost and demand flexibility scenarios when the overall demand elasticity equals 2.



The graph shows the difference in total economic surplus with a 100 percent renewable system versus the baseline scenario given on the horizontal axis, holding all else the same. Total surplus change is reported as a percentage of baseline expenditure on electricity. The graph depicts all scenarios with an overall demand elasticity of 2 instead of 0.1 as reported in the main paper. The top row shows the value of variable pricing under current costs; the bottom row shows the value of variable pricing under projected future costs (2045). The horizontal axis shows the policy scenario: fossil, 100% renewable or unconstrained (maximum surplus, regardless of source). The bars show the baseline case with 50 percent electric vehicle fleet and 2045 load profile, the diamonds show the 2007 load profile, and the error bars show how results differ with 0.5 percent and 100 percent electric vehicles–more electric vehicles always increase the value of variable pricing.

Table A.1: Supplementary Results: Surplus changes relative to baseline if actual loads from 2007.

(1) Policy Objective	(2) Cost	(3) Demand Flexibility	(4) Pricing	(5) % Renewable	(6) Price ($/MWh)	(7) Mean Q (MWh/hr.)	(8) SD of Price ($/MWh)	(9) Δ CS (%.)	(10) Δ EV Cost (%)	(11) Δ PS (%)	(12) Δ TS (%)	(13) Δ CS Highflex (%)	(14) Δ CS Midflex (%)	(15) Δ CS Inflex (%)	(16) Δ TS Dyn (%)
Fossil	Current	Optimistic	Flat	3.78	91	1043	0	32.7	-28.6	8.2	40.9	27.8	27.8	27.8	4.6
			Dynamic	3.64	63	1085	4	57.7	-56.6	-12.2	45.5	50.9	50.9	50.9	
		Pessimistic	Flat	3.78	91	1043	0	32.6	-27.1	8	40.7	28.3	28.3	28.3	3.7
			Dynamic	3.65	61	1084	0	56.4	-56.1	-12	44.4	53	50.4	50.2	
	Future	Optimistic	Flat	3.90	125	1005	0	Baseline							3.9
			Dynamic	3.89	121	1007	11	4.4	-10.4	-0.6	3.9	2.3	2.3	2.3	
		Pessimistic	Flat	3.90	125	1004	0	Baseline							3
			Dynamic	3.91	116	1004	10	0.4	-13.2	2.6	3	7.6	-1.3	-2	
100% Renewable	Current	Optimistic	Flat	100	171	967	0	-41.1	40.7	1.3	-39.8	-36.4	-36.4	-36.4	23.7
			Dynamic	100	128	1063	87	-12.2	-14.4	-3.9	-16.1	3.1	-16.1	-26	
		Pessimistic	Flat	100	172	967	0	-39.1	39.6	-0.4	-39.5	-36.5	-36.5	-36.5	13.4
			Dynamic		133	1034	91	-22.2	-14.8	-3.9	-26.1	7.5	-16.1	-26.9	
	Future	Optimistic	Flat	100	98	1033	0	25.3	-29.5	-25.7	-0.4	21.4	21.4	21.4	13.5
			Dynamic	100	84	1159	75	39	-51.3	-25.9	13.1	43.1	30.8	26.4	
		Pessimistic	Flat	100	98	1033	0	25.3	-28.2	-25.7	-0.4	22	22	22	8.4
			Dynamic	100	92	1127	82	33.5	-49.9	-25.5	8	44.6	31	26.6	
Unconstrained	Current	Optimistic	Flat	3.68	72	1072	0	49.6	-44.9	-8.7	41	43.3	43.3	43.3	5.7
			Dynamic	6.24	74	1067	7	47.9	-48.8	-1.2	46.7	41.8	41.8	41.8	
		Pessimistic	Flat	3.68	70	1072	0	49.4	-43.4	-8.7	40.7	45.6	45.6	45.6	3.7
			Dynamic	3.65	61	1083	0	55.9	-56.1	-11.5	44.4	53	50	49.7	
	Future	Optimistic	Flat	74	88	1046	0	34.4	-34.7	-4.4	30	30	30	30	8.8
			Dynamic		72	1105	38	44.1	-53.7	-5.3	38.8	45.6	38.7	34.5	
		Pessimistic	Flat	74	88	1046	0	34.4	-33.3	-4.6	29.8	30.6	30.6	30.6	5.3
			Dynamic	81	80	1085	42	38.2	-52.2	-3.1	35.1	45.9	35.2	31.2	

Notes: Like table 3.4, except baseline demand is tied to actual 2007 loads, not projected loads for 2045.

Table A.2: Supplementary Results: Surplus changes relative to baseline if fewer electric vehicles (0.5 percent).

(1) Policy Objective	(2) Cost	(3) Demand Flexibility	(4) Pricing	(5) % Renewable	(6) Price ($/MWh)	(7) Mean Q (MWh/hr.)	(8) SD of Price ($/MWh)	(9) Δ CS (%.)	(10) Δ EV Cost (%)	(11) Δ PS (%)	(12) Δ TS (%)	(13) Δ CS Highflex (%)	(14) Δ CS Midflex (%)	(15) Δ CS Inflex (%)	(16) Δ TS Dyn (%)
Fossil	Current	Optimistic	Flat	4.39	60	982	0	54	-54.2	-17.3	36.7	54.5	54.5	54.5	2.6
			Dynamic	4.30	50	1002	1	63.2	-61.8	-23.9	39.3	62.9	62.8	62.8	
		Pessimistic	Flat	4.51	77	955	0	38.8	-44.8	-2.8	36.1	39.8	39.8	39.8	2.4
			Dynamic	4.35	49	990	1	56.7	-63.7	-18.2	38.5	63.9	56.7	55.8	
	Future	Optimistic	Flat	4.76	126	904	0	Baseline							2.5
			Dynamic	4.70	120	911	12	7.1	-14.1	-4.7	2.5	5.2	4.7	4.7	
		Pessimistic	Flat	4.76	126	904	0	Baseline							1.1
			Dynamic	4.74	111	908	5	3.4	-18.4	-2.4	1.1	12	3.4	2.5	
100% Renewable	Current	Optimistic	Flat	100	164	876	0	-29.2	31.1	-7.1	-36.3	-29.6	-29.6	-29.6	17.7
			Dynamic	100	126	961	86	-12.5	-14.2	-6.1	-18.6	5.7	-13.6	-23	
		Pessimistic	Flat	100	161	877	0	-29.3	23.6	-6.8	-36.1	-27.3	-27.3	-27.3	8.2
			Dynamic	100	134	936	95	-23.2	-19.9	-4.7	-27.9	10	-15.3	-26.4	
	Future	Optimistic	Flat	100	98	931	0	22.9	-25.1	-29.6	-6.7	22.5	22.5	22.5	11.1
			Dynamic	100	84	1043	74	34.2	-48.1	-29.8	4.4	44.4	31.4	27.2	
		Pessimistic	Flat	100	98	931	0	22.9	-25.1	-29.6	-6.7	22.6	22.6	22.6	6
			Dynamic	100	91	1008	80	29.2	-49.7	-29.9	-0.7	46	31.7	27.5	
Unconstrained	Current	Optimistic	Flat	4.49	76	960	0	41.8	-29.5	-5.3	36.4	40.7	40.7	40.7	4.4
			Dynamic	4.34	57	987	5	56.7	-59.3	-15.9	40.8	57.6	57.1	57.1	
		Pessimistic	Flat	4.39	61	982	0	54.3	-54.4	-17.6	36.6	53.2	53.2	53.2	1.7
			Dynamic	4.34	49	993	1	57.8	-63.7	-19.5	38.3	63.9	58.1	57.4	
	Future	Optimistic	Flat	75	93	937	0	26.1	-27.7	-0.4	25.6	26.8	26.8	26.8	6.8
			Dynamic		71	995	32	40.2	-50.7	-7.8	32.4	46.8	38.6	35.6	
		Pessimistic	Flat	75	93	936	0	26.4	-27.8	-0.7	25.6	26.4	26.4	26.4	3
			Dynamic	76	79	973	38	33.9	-51.7	-5.2	28.6	47.5	36	32.3	

Notes: Like table 3.4, except the share of electric vehicles is 0.5% (the current share of the fleet) instead of 50%.

Table A.3: Supplementary Results: Surplus changes relative to baseline if more electric vehicles (100 percent).

(1) Policy Objective	(2) Cost	(3) Demand Flexibility	(4) Pricing	(5) % Renewable	(6) Price ($/MWh)	(7) Mean Q (MWh/hr.)	(8) SD of Price ($/MWh)	(9) Δ CS (%.)	(10) Δ EV Cost (%)	(11) Δ PS (%)	(12) Δ TS (%)	(13) Δ CS Highflex (%)	(14) Δ CS Midflex (%)	(15) Δ CS Inflex (%)	(16) Δ TS Dyn (%)
Fossil	Current	Optimistic	Flat	3.77	91	941	0	34.9	-31.8	10.4	45.3	27.4	27.4	27.4	6.4
			Dynamic	3.71	77	958	5	48.3	-41.3	3.5	51.7	38.9	38.9	38.9	
		Pessimistic	Flat	3.77	91	941	0	32.4	-22	13	45.5	27.1	27.1	27.1	6.3
			Dynamic		75	956	0	47.6	-45.6	4.2	51.8	41.1	38.1	37.8	
	Future	Optimistic	Flat	3.88	125	905	0	Baseline							4.5
			Dynamic	3.88	121	907	10	3.1	-5.3	1.4	4.5	3.2	3.2	3.2	
		Pessimistic	Flat	3.88	124	905	0	Baseline							4.5
			Dynamic	3.87	121	910	11	5.8	-10.9	-1.3	4.5	2.6	2.4	2.4	
100% Renewable	Current	Optimistic	Flat	100	166	872	0	-42.2	33.8	-2.3	-44.5	-32.7	-32.7	-32.7	29
			Dynamic	100	128	957	88	-13	-9.7	-2.5	-15.5	3.4	-16.3	-25.5	
		Pessimistic	Flat	100	171	871	0	-41.9	29.6	-2.8	-44.7	-37	-37	-37	19.9
			Dynamic	100	137	930	96	-24.9	-13.4	0.1	-24.8	4.7	-19	-30.3	
	Future	Optimistic	Flat	100	98	931	0	26.4	-24.5	-26.7	-0.4	21.6	21.6	21.6	16.2
			Dynamic	100	85	1048	75	42.6	-46.7	-26.8	15.8	43	31.1	26.2	
		Pessimistic	Flat	100	98	931	0	27	-28	-27.4	-0.4	21.3	21.3	21.3	11.2
			Dynamic	100	93	1021	83	37.9	-50.3	-27.1	10.8	44.3	30.7	25.5	
Unconstrained	Current	Optimistic	Flat	3.93	75	960	0	49.5	-36	-4.1	45.4	41	41	41	6.4
			Dynamic	6.09	73	962	4	52.5	-44.6	-0.7	51.8	42.7	42.7	42.7	
		Pessimistic	Flat	4.67	89	941	0	33.4	-19.9	12.1	45.5	28.7	28.7	28.7	6.3
			Dynamic	5.88	72	961	4	49.8	-49.6	2	51.8	42.9	41.5	41.4	
	Future	Optimistic	Flat	74	89	942	0	35.9	-30.3	-2.8	33.1	29.7	29.7	29.7	11.5
			Dynamic	81	73	993	36	47.9	-48.4	-3.3	44.6	44.4	36.5	33.2	
		Pessimistic	Flat	75	88	942	0	36.6	-34.1	-3.3	33.3	29.7	29.7	29.7	7.8
			Dynamic	81	80	977	41	43.8	-53	-2.7	41.1	45.6	35.1	31	

Notes: Like table 3.4, except the share of electric vehicles is 100% instead of 50%.

Table A.4: Supplementary Results: Surplus changes if overall demand elasticity = 0.5

(1) Policy Objective	(2) Cost	(3) Demand Flexibility	(4) Pricing	(5) % Renewable	(6) Price ($/MWh)	(7) Mean Q (MWh/hr.)	(8) SD of Price ($/MWh)	(9) Δ CS (%.)	(10) Δ EV Cost (%)	(11) Δ PS (%)	(12) Δ TS (%)	(13) Δ CS High-flex (%)	(14) Δ CS Midflex (%)	(15) Δ CS Inflex (%)	(16) Δ TS Dyn (%)
Fossil	Current	Optimistic	Flat	3.11	82	1283	0	48.4	-38.2	2.5	50.9	35.1	35.1	35.1	5.1
			Dynamic	2.68	61	1508	2	77.7	-59.7	-21.6	56	53.4	53.4	53.4	
		Pessimistic	Flat	3.11	84	1283	0	45.6	-36	5.3	50.9	33.5	33.5	33.5	1.9
			Dynamic	2.46	49	1648	0	90	-66.5	-37.2	52.8	63.5	61.9	61.7	
	Future	Optimistic	Flat	3.76	125	1043	0				Baseline				3.7
			Dynamic	3.80	127	1033	4	-0.4	-6.1	4.1	3.7	-2	-2	-2	
		Pessimistic	Flat	3.76	125	1043	0				Baseline				2.8
			Dynamic	3.64	107	1083	0	9.1	-20	-6.3	2.8	14.3	6.9	6.4	
100% Renewable	Current	Optimistic	Flat	100	171	888	0	-43.6	39.9	0.5	-43.1	-36.2	-36.2	-36.2	31.4
			Dynamic	100	128	1064	62	-11.5	-15.5	-0.1	-11.7	1.8	-19.5	-28.3	
		Pessimistic	Flat	100	173	886	0	-45.3	39.9	2.1	-43.1	-37.2	-37.2	-37.2	20.1
			Dynamic	100	138	989	80	-27.9	-13	4.9	-23	3.2	-21.4	-32.3	
	Future	Optimistic	Flat	100	102	1159	0	26.8	-27.9	-26.2	0.6	18.8	18.8	18.8	22.4
			Dynamic	100	82	1370	37	48.6	-53.2	-25.6	23	42.3	29.1	25.2	
		Pessimistic	Flat	100	102	1159	0	24.5	-26	-23.9	0.6	18.8	18.8	18.8	15.4
			Dynamic	100	91	1277	41	38.4	-50.8	-22.4	16	43	28.8	24.7	
Unconstrained	Current	Optimistic	Flat	3.23	83	1283	0	48.3	-37.7	2.7	50.9	34.1	34.1	34.1	5.2
			Dynamic	2.67	60	1509	2	78.5	-60	-22.5	56.1	53.6	53.6	53.6	
		Pessimistic	Flat	3.23	84	1283	0	45.4	-35.2	5.5	50.9	33.5	33.5	33.5	3.6
			Dynamic	2.56	50	1581	1	84	-66.4	-29.5	54.5	63.2	57.7	57.2	
	Future	Optimistic	Flat	76	94	1205	0	35.8	-33.7	-0.4	35.4	25	25	25	14.2
			Dynamic	84	76	1366	21	52.4	-53.4	-2.9	49.6	42.9	33.6	30.6	
		Pessimistic	Flat	77	95	1204	0	32.5	-31	3	35.4	24.8	24.8	24.8	8.4
			Dynamic	81	88	1272	33	40.1	-52.3	3.7	43.8	44.1	29.9	26.6	

Notes: Like table 3.4, except the the overall demand elasticity (θ) equals 0.5 instead of 0.1

Table A.5: Supplementary Results: Surplus changes if overall demand elasticity = 0.9

(1) Policy Objective	(2) Cost	(3) Demand Flexibility	(4) Pricing	(5) % Renewable	(6) Price ($/MWh)	(7) Mean Q (MWh/hr.)	(8) SD of Price ($/MWh)	(9) Δ CS (%.)	(10) Δ EV Cost (%)	(11) Δ PS (%)	(12) Δ TS (%)	(13) Δ CS Highflex (%)	(14) Δ CS Midflex (%)	(15) Δ CS Inflex (%)	(16) Δ TS Dyn (%)
Fossil	Current	Optimistic	Flat	2.43	86	1673	0	50.9	-22.1	10.6	61.6	32.8	32.8	32.8	10.2
			Dynamic	2.22	78	1840	3	66.7	-46.6	5.1	71.8	39.6	39.5	39.5	
		Pessimistic	Flat	2.43	86	1673	0	51	-22.2	10.7	61.7	32.7	32.7	32.7	8.9
			Dynamic	2.28	66	1791	4	63.8	-56.2	6.8	70.6	49.9	37.8	36.1	
	Future	Optimistic	Flat	3.34	127	1187	0	Baseline							4
			Dynamic	3.37	128	1179	3	-0.4	-7	4.4	4	-0.7	-0.7	-0.7	
		Pessimistic	Flat	3.34	127	1188	0	Baseline							3.2
			Dynamic	3.24	112	1230	0	6.1	-18.8	-2.8	3.2	12.1	3.4	2.8	
100% Renewable	Current	Optimistic	Flat	100	170	903	0	-44.4	35.1	-1.7	-46.1	-33.2	-33.2	-33.2	35.7
			Dynamic	100	128	1155	45	-14.2	-16.2	3.7	-10.4	3.1	-18.3	-27	
		Pessimistic	Flat	100	169	923	0	-40.1	28.3	-6.1	-46.3	-32.6	-32.6	-32.6	23.5
			Dynamic	100	138	1032	65	-27.9	-15.9	5.1	-22.8	3.7	-19.8	-30.6	
	Future	Optimistic	Flat	100	102	1440	0	30.4	-28	-25.4	5	19.6	19.6	19.6	28.9
			Dynamic	100	82	1818	28	56.5	-52.7	-22.5	33.9	42.6	29.1	25.5	
		Pessimistic	Flat	100	102	1440	0	30.5	-28.2	-25.5	5	19.4	19.4	19.4	19.7
			Dynamic	100	91	1641	34	46.7	-52.5	-22	24.7	43.2	29	25.3	
Unconstrained	Current	Optimistic	Flat	2.44	87	1673	0	50.4	-22.6	11.2	61.6	32.4	32.4	32.4	10.5
			Dynamic	7.49	75	1912	3	72.5	-49	-0.4	72.1	42.3	42.3	42.3	
		Pessimistic	Flat	2.44	87	1673	0	50.4	-22.7	11.2	61.7	32.2	32.2	32.2	9
			Dynamic	3.22	64	1803	3	64.3	-57.5	6.4	70.7	51.9	38.1	36.2	
	Future	Optimistic	Flat	81	98	1493	0	35.4	-29.9	5.5	40.9	22.8	22.8	22.8	
			Dynamic	87	78	1834	20	59.5	-53.1	0.9	60.4	43.1	31.8	29	19.5
		Pessimistic	Flat	81	99	1491	0	36.3	-30.6	4.7	41	22.5	22.5	22.5	11
			Dynamic	85	90	1642	30	47.8	-53.5	4.2	52	43.9	29.4	26.3	

Notes: Like table 3.4, except the the overall demand elasticity (θ) equals 0.9 instead of 0.1

Table A.6: Supplementary Results: Surplus changes if overall demand elasticity = 2

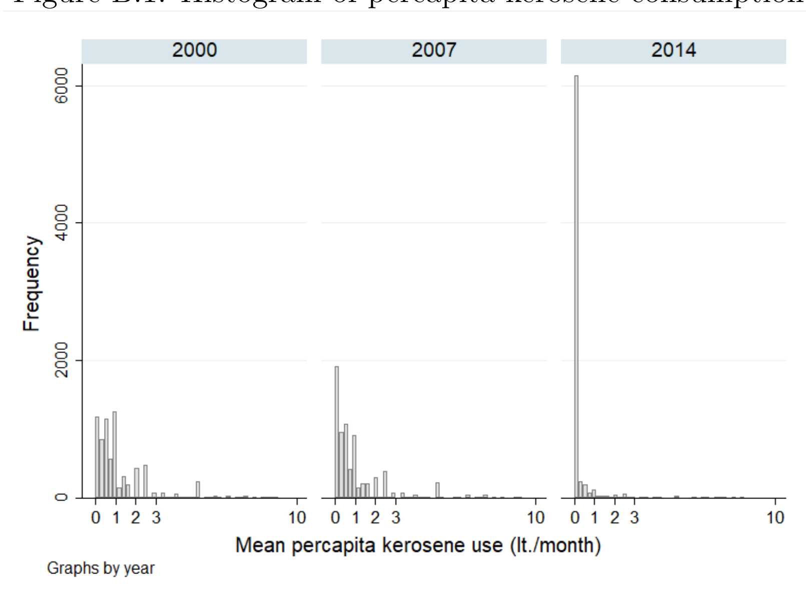
(1) Policy Objective	(2) Cost	(3) Demand Flexibility	(4) Pricing	(5) % Renewable	(6) Price ($/MWh)	(7) Mean Q (MWh/hr.)	(8) SD of Price ($/MWh)	(9) Δ CS (%.)	(10) Δ EV Cost (%)	(11) Δ PS (%)	(12) Δ TS (%)	(13) Δ CS Highflex (%)	(14) Δ CS Midflex (%)	(15) Δ CS Inflex (%)	(16) Δ TS Dyn (%)
Fossil	Current	Optimistic	Flat	1.78	110	2324	0	33.5	-2.4	48.6	82.2	14.9	14.9	14.9	10.8
			Dynamic	1.64	104	2522	4	45.6	-21	47.5	93	19.4	19.1	19.1	
		Pessimistic	Flat	1.78	110	2324	0	33.6	-10.2	48.4	82	15.1	15.1	15.1	9.1
			Dynamic	1.65	92	2512	7	47.1	-39.6	44	91.1	30	19.5	18.1	
	Future	Optimistic	Flat	2.42	128	1672	0	Baseline							5.5
			Dynamic	2.33	126	1742	4	4.1	-3.2	1.4	5.5	2	1.8	1.8	
		Pessimistic	Flat	2.42	129	1673	0	Baseline							4.7
			Dynamic	2.30	115	1772	5	6.5	-21.6	-1.8	4.7	11.5	2.9	2.1	
100% Renewable	Current	Optimistic	Flat	100	168	967	0	-50	38.3	-3.4	-53.3	-30.6	-30.6	-30.6	43.1
			Dynamic	100	126	1471	30	-17.4	-10.4	7.2	-10.2	4.5	-18.2	-26.6	
		Pessimistic	Flat	100	171	945	0	-53	36.7	-0.1	-53.1	-32.6	-32.6	-32.6	27.6
			Dynamic	100	138	1156	50	-34.5	-17.8	9	-25.5	5.5	-19.9	-29.1	
	Future	Optimistic	Flat	100	117	2043	0	20.8	-9.6	-2.1	18.7	9	9	9	46.9
			Dynamic	100	100	2659	25	45.3	-32	20.3	65.6	27.1	13.6	10.5	
		Pessimistic	Flat	100	117	2043	0	20.9	-17.4	-2.3	18.6	9.3	9.3	9.3	32.1
			Dynamic	100	104	2515	30	43.6	-43.5	7.1	50.7	33	18.7	15.6	
Unconstrained	Current	Optimistic	Flat	9.28	107	2382	0	37.7	-4.6	45.7	83.5	17.1	17.1	17.1	16.6
			Dynamic	23.42	105	2503	6	44.4	-18.9	55.8	100.1	18.5	18.3	18.3	
		Pessimistic	Flat	9.28	107	2382	0	37.9	-12.5	45.4	83.3	17.2	17.2	17.2	12.5
			Dynamic	13.47	88	2546	4	46.7	-40	49.1	95.8	32.5	19.8	17.8	
	Future	Optimistic	Flat	80	103	2563	0	47.4	-19.4	14.6	62	19.9	19.9	19.9	33.2
			Dynamic	89	97	2820	21	53	-34	42.2	95.2	29.4	16.9	14.1	
		Pessimistic	Flat	80	104	2563	0	47.9	-27.3	13.9	61.8	19.7	19.7	19.7	17.7
			Dynamic	90	101	2638	28	49.8	-46.1	29.7	79.5	35.3	20.8	17.9	

Notes: Like table 3.4, except the the overall demand elasticity (θ) equals 2 instead of 0.1

Appendix C

Appendix to Chapter 4

Figure B.1: Histogram of percapita kerosene consumption



This figure shows the distribution of households based on their percapita kerosene consumption on each survey wave.

Table A.1: Test of parallel time trends

	(1) Percapita kerosene quantity (litre)	(2) Log kerosene price	(3) Log nondurables exp.	(4) Log food exp.	(5) Log utilities bills
ProgramX2007	-0.239	-0.008	0.213	0.146	0.004
	(0.491)	(0.175)	(0.249)	(0.142)	(0.119)
Constant	1.181	8.451***	11.754***	12.583***	10.767***
	(0.965)	(0.203)	(0.565)	(0.210)	(0.295)
Obs.	10,224	8,371	10,168	10,189	10,018
R^2 stat	0.512	0.903	0.710	0.702	0.802
Household FE	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y

Sample is prior to the program. All regressions include district fixed effects and year dummies. The standard error is clustered by district.

Table A.2: Effect of the program on kerosene purchased, with alternative control groups

	(1)	(2)	(3)	(4)	(5)	(6)
	Early vs Untreated		Late vs Untreated		Early vs Late Treated	
Panel A. Before the program						
ProgramX2007	0.171	-0.374	1.239	0.697	-0.331	-0.164
	(0.318)	(0.507)	(0.946)	(1.354)	(0.485)	(0.629)
Obs.	8,745	8,745	1,948	1,948	9,766	9,766
R^2 stat	0.036	0.514	0.029	0.506	0.034	0.511
Panel B. Full sample						
ProgamX2014	-1.596***	-1.775***	-1.643**	-1.965	-0.235	-0.062
	(0.499)	(0.659)	(0.646)	(1.412)	(0.295)	(0.360)
Obs.	13,003	13,003	2,886	2,886	14,517	14,517
R^2 stat	0.041	0.357	0.023	0.343	0.037	0.353
District FE	Y		Y		Y	
Household FE		Y		Y		Y
Month FE		Y		Y		Y

As the treatment group, column 1-2 and 5-6 use early treated households, and column 3-4 use late treated households. As the control group, column 1-4 use untreated households, and column 5-6 use late treated households. Panel A uses sample prior to the program to show pre-implementation trend between treatment and control groups. Panel B uses full sample to look at the program effect on the percapita kerosene quantity purchased (litre) (β_3 coefficient from Eq. 4.1). The standard error is cluster by district.

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